Cognitive Content Recommendation in Digital Knowledge Repositories – a Survey of Recent Trends

Andrzej M.J. Skulimowski

[1]AGH University of Science and Technology, Chair of Automatic Control and Biomedical Engineering, Decision Science Laboratory, 30-050 Kraków, Poland
[2]International Centre for Decision Sciences and Forecasting, Progress & Business Foundation, 30-048 Kraków, Poland
e-mail: ams@agh.edu.pl

Abstract. This paper presents an overview of the cognitive aspects of content recommendation process in large heterogeneous knowledge repositories. It also covers applications to design algorithms of incremental learning of users' preferences, emotions, and satisfaction. This allows the recommendation procedures to align to the present and expected cognitive states of a user, increasing combined recommendation and repository use efficiency. The learning algorithm takes into account the results of the cognitive and neural modelling of users' decision behaviour. Inspirations from nature used in recommendation systems differ from the usual mimicking of biological neural processes. Specifically, a cognitive knowledge recommender may follow a strategy to discover emotional patterns in user behaviour and then adjust the recommendation procedure accordingly. The knowledge of cognitive decision mechanisms helps to optimize recommendation goals. Other cognitive recommendation procedures assist users in creating consistent learning or research groups. The anticipated primary application field of the above algorithms is a large knowledge repository coupled with an innovative training platform developed within the ongoing Horizon 2020 research project.

Keywords: Research recommenders, scientific big data, Personal Learning Environments, preference modelling, mobile and ubiquitous learning

1 Introduction

Cognitive and biological inspirations are increasingly common in the design of advanced software systems. This is due to the fact that basic biological observations and the knowledge of cognitive mechanisms intervene in the background of virtually all creative processes. These include the design and implementation of web applications, where interaction with users plays a primary role.

This paper presents research on eliciting optimal functional architectures of recommendation systems supporting users of scientific and learning repositories. Such systems are expected to facilitate the use of large scientific knowledge bases and their future successors - global expert systems (GESs, cf. [37], [39]). The latter will ensure access to all web-based knowledge sources, including data and multimedia repositories as well as the Internet of Things (IoT)-based real-time data streams from

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sensors and actuators. GESs will also encompass real-time and archive information concerning human and artificial users of mutually connected social networks. The emergence of GESs and their impact on the future of scientific research has been studied recently in [37], [39] and [40]. The above-cited research reveals a growing need to support the users of heterogeneous large-scale repositories while searching, classifying, analysing, managing and further using the retrieved content. Appropriate software agents endowed with the usual expert system functionalities to support users of large-scale scientific repositories can greatly increase the efficiency of users' interaction with such systems, cf. e.g. [17],[21], [25],[26].[49]. We will argue that the ability of such agents to align with the individual user cognitive phenomena determines a most promising development trend of such applications [14].

The agents will address issues related to the following general development trends of scientific repositories, which have been identified and studied in [40, Chapters 5 and 8], and investigated further in [39] and in H2020 project MOVING [19]:

- a growing number of users with an increasing diversification of individual preferences and learning goals,
- a growing number of interconnected knowledge units,
- a growing diversity of content stored in knowledge repositories,
- a growing level of integration of heterogeneous information sources,
- an increase in the amount of information and sophistication of information processing within individual units,
- a growing mean intensity of information exchange (in bauds) and the total amount of information exchanged within an individual session (in bits),
- a rapidly growing need to assist users by informed recommendation of content and services of knowledge repositories.

The above trends are the main reason for the growing complexity of research and learning supporting applications, including recommenders. The need to acquire knowledge on new functionalities and corresponding user skills is at the same time a key source of difficulty when these systems are used by learners. This is why identifying the learner's momentary emotional state by the learning application [31], [32] can be as relevant as the elicitation of users' preferences to be used by learning and research recommender systems. This paper studies the related issues in the context of selecting the best recommendation methods.

Due to a close relationship between the decision support (DSS) and recommendation systems, cognitive research and/or learning recommenders can benefit from the existing contributions of the cognitive DSS theory and implementation experience. It turns out that the cognitive science inspirations [28], [48] are becoming common in open and distance learning environments. They often occur in the design of various advanced learning software systems.

The results presented here should contribute towards designing automatic decision pilots, a subclass of cognitive recommenders, providing rankings and implementing constraints, but not the final choice. They have been studied with the aim to facilitate the use of a large innovative knowledge repository storing mostly scientific papers, massive open online courses (MOOCs) and economic information (cf. [24]). Content-based recommendation for this repository, including performance measurements and a comparison of 12 approaches focused on methods of scientific papers recommending in the area of the economy has been recently presented in the above-cited paper [24]. Other methods of recommending learning and research-related content are also discussed in [2], [8], [25], and [26]. Issues related to distance learning are studied in [28] and [48].

2 Cognitive Inspirations of Recommender Systems

We will start this section by presenting a formal background to recommendation systems, which will be useful in defining a family of recommenders best fitting the needs of knowledge repositories.

2.1 Background to recommendation systems

A general single set recommendation problem can be formulated in the following way:

$$(F{:}U\supset U_0\rightarrow I\!R^n)\rightarrow min(P) \tag{1}$$

$$(G{:}2^V \times \Pi \rightarrow I\!R^m)\rightarrow min(Q),\ V{:}=\{(u,f(u)){:}u\in U,\ f(u)\in I\!R^p\} \tag{2}$$

$$C \subset argmin\{F^*(u){:}u\in U_0 \cup argmin\{G(V_r,\pi_r)\}\}, \tag{3}$$

where $F=(F_1,\ldots,F_n)$ and $G=(G_1,\ldots,G_m)$ are vector performance criteria, the first of the decision maker D who selects items from a certain subset U_0 of the set of all admissible or available items U; the second of the recommendation system owner $S(\mathcal{R})$. Eq. (1) describes the item selection problem without recommendation, where the set U_0 contains admissible items D is initially aware of or with features known to D. We assume that the function F may be represented as a composition of a selection function F^* defined on a set of characteristics of items from U_0 expressed by certain features, and a function f associating features to items, i.e. $F=F^*\circ f$.

The recommender $\mathcal{R}$ is an artificial agent that recommends a subset V of admissible items to the decision maker D together with information about their p features represented numerically for data processing. It is assumed that D takes into account the same features of items from the subset U_0 known to D prior to the recommendation. It can be an essential subset of U.

When recommending admissible items to D, the recommender $\mathcal{R}$ takes into account an estimation π_r of D's preference structure P from the set of all feasible preference structures Π. By definition, a preference structure is a partial ordering of $F(U_0)$ conforming to the natural componentwise order in $I\!R^n$. Similarly, the subset V is selected according to the preference structure Q of the recommendation system owner $S(\mathcal{R})$. In this case Q conforms to the natural componentwise order in $I\!R^m$. In this paper we will not study in detail the course of the estimation process and the properties of Π, focussing on the cognitive aspects of recommendation and on digital repository applications. The final choice C of the decision maker D depends on D's preference structure P and on the recommendation that is modelled by eq. (3).

In the most common case, where a recommender presents an ordered sequence of at most K items to a potential customer, the union of sets of all k-permutations of U, for $k=1,2,\ldots K \leq \#U$, is used instead of 2^U, i.e. the second equation of the recommendation problem (1)-(3) is replaced by

$$(G\colon \bigcup_{i\leq 1\leq K} U^i \times \Pi \to I\!R^m) \to min(Q) \tag{4}$$

yielding a ranking-based recommendation problem (1),(4),(3) with similar solution principles as in the problem (1)-(3).

Both recommendation processes exemplify multicriteria recommenders that have been studied e.g. in [1], [22]. While D makes decisions usually taking into account $n>1$ criteria, the goal of a recommendation system is most often to maximize its owner's profit so that frequently $p=1$ [7]. When recommending items from a not-for-profit or institutional subscription-based knowledge repository, it is likely that the sets of criteria $\{G_1,\ldots,G_n\}$ and $\{F_1,\ldots,F_n\}$ coincide or overlap considerably. This is the case when G includes indices describing the efficiency of the learning or research process that are also followed by the users. For example, the repository content recommender may be designed to optimize recommendation criteria such as:

- the degree of representativeness of scholarly literature necessary to complete a specific research or learning task,
- the precision of the recommended literature set (with respect to the user's learning goal),
- the goodness of fit of recommended courses to the individual learning preferences,
- increasing the creativity of learners beyond the momentary learning goal [34].

To create a common base for classifying intelligent agents, including cognitive recommenders and autonomous decision-making systems, in [36] we defined the three levels of freewill. Freedom of choice of the 1st order is the ability to choose when a set of choice criteria for a given set of admissible alternatives is specified; freedom of choice of the 2nd order allows the decision maker to relax the constraints; freedom of choice of the 3rd order is the power to select one's criteria of choice in the feature space of real-life objects selected by an intelligent artificial agent.

According to the above taxonomy, recommenders are autonomous systems of the 1st or 2nd order, depending on whether implementation allows the agent to seek for information in the open web [12]. This is not allowed for the knowledge repository presented here, however. In addition, recommenders are given the capacity to learn from their past decision and efficiency experience.

2.2 Research issues in cognitive recommendation and decision support

The predominant mechanism of cognitive inspiration in recommendation systems is somehow different than the usual mimicking of living systems. As evidenced by the results of a recent foresight project [40, Ch.4], the overall development trend of recommender systems follows a strategy to discover the cognitive aspects of user behaviour and adjust the recommendation procedures correspondingly, so that the recommendation goals are optimized [3], [27].

During the last two decades, the theory of recommenders has become an interdisciplinary research field [4], [40, Ch.4] situated partly within the following areas:

- decision science, specifically modelling real-life decision problems and processes,
- computer science in terms of the implementation and computer architecture of recommenders and decision support systems, both regarded as a subclass of intelligent systems,
- cognitive science and mathematical psychology.

Although decision processes related to applying recommendations involve the highest-level cognitive function of the human mind, their appurtenance to cognitive science is sometimes neglected when designing recommender systems. The reasons for that are threefold:

1. The partitioned character of research on elicitation and modelling of human preferences, where the psychometric research does not meet prevailing theoretical studies on decision analysis, and recommender systems are designed without paying enough attention to real-life human decision-making mechanisms;
2. The tendency to restrict modelling human decisions to cases where the decision maker(s) is either able to formulate criteria of choice or explicitly define a set of admissible alternatives. What follows is a mathematical programming or gaming problem, and subsequent efforts are focussed on solving it, without taking care about cognitive phenomena such as rapidly changing preferences, an extension/contraction of the decision scope resulting from different cognitive processes.
3. The lack of adequate decision models when the information underlying the decision making has a multimedia form. In such situations autonomous learning support systems need to elicit users' preferences concerning the sequence and relevance hierarchy of learning goals. These, in turn, can be used for further recommendations after being implemented in tailored recommender systems.

Further drawbacks concerning the current state of research on decision models for recommendation systems originate from the relatively low linkage of recommendation-suitable models to the theory of decision support systems (DSSs). This issue can be described as follows:

- The difficulty in applying decision-making procedures arises in situations where the decision maker's preference structure is non-compatible with the data available or must be gradually elicited. Awareness of the relevance of using cognitive decision-making mechanisms to increase the efficiency and adequacy of recommendation in the above-mentioned situations is still insufficient.
- The application of a variety of so-called interactive decision-making algorithms that are very popular in multicriteria DSSs can face different problems in recommenders [32] where decisions are made quickly, leaving no space for

a long dialogue as is usual in interactive DSSs. In addition, processing such a dialogue does not guarantee final success in the form of convergence to a satisfactory compromise learning plan. The convergence conditions of the interactive procedures may be non-applicable to the process of cognitive decision making, neglecting spontaneous discoveries of potential solutions better than the next candidate for compromise solution generated by the formal procedure. Even a simple ‘change of mind’ by the decision maker during the procedure can perturb convergence.

- Unlike the human expert advising, who is capable of mitigating the results of incorrect recommendations, the existing recommenders act according to the principle that once an item is selected, and this choice is registered, the role of the expert system is finished. When external circumstances that have influenced the choice change, the decision maker might wish further assistance to re-examine the choice, and sometimes change the decision. This is not straightforward in recommender systems, and the decision maker must usually repeat the whole procedure.
- The crucial role of the ability to learn based on previous choices estimating the emotions of decision makers, cf. [14], [31].

Despite the above, it should be observed that the appearance of cognitive phenomena has recently contributed to a remarkable change in the practice as well as in the philosophy of designing recommendation systems [50].

3. Principles of cognitive content recommenders

When selecting recommendation principles most suitable for a learning platform, we will refer to the commonly approved taxonomy of recommendation methods, such as the breakdown into collaborative filtering and content (or item) based recommendation [4], [5]. In addition, the functionalities of specialized recommenders designed for content recommendation in knowledge repositories, learning platforms and learning management systems (LMSs), should be split into content searching filtering and user presentation (knowledge extraction and processing), and in recommending learning activities, following the phases of a holistic preference learning process.

Learning recommendation algorithms may recommend tangible items (research papers, laboratories, courses, books, videos) as well as intangibles, actions to be taken, or other users or groups of them as research or learning partners, cf. e.g. [10], [15], [16], [23], [29], [42]. Here, *items* denote either:

- Digital documents, such as research papers or books;
- Online courses, including MOOC, or educational games;
- Quantitative or qualitative datasets;
- Videos and graphic digests;
- Laboratories;
- Research or learning-oriented software.

Content-based recommendation is a natural way of recommending these items, but social and other recommendation modes can also be used. Collaborative filtering may be misleading as the most used (or most cited) items do not necessarily have to satisfy the needs of a particular user [5]. Similarly, a big diversification of research and learning goals makes it difficult to apply the similarity of user activities when using knowledge repository items. Furthermore, the recommendations may be hybrid [8] or complex, pointing out objects, actions, and/or persons at one time.

For a given collection of recommended items stored in a knowledge repository, we will investigate the following content recommendation problems:

- Direct item or content based recommendation by providing a list of items (problem (1)-(3), in some cases also (1),(4),(3)),
- Indirect content recommendation by providing a query extension to the user.

The latter problem can be converted to the first by considering the anticipated properties [38] of search results with the recommended query. Based on an analysis of current approaches to learning and research recommendation, we will specify automatic decision pilots, a subclass of cognitive content-based recommenders. Decision pilots provide sets or rankings of items and implement constraints, while the final choice is performed by a user. Finally, we will propose a hybrid cognitive recommendation engine, endowed with supervised learning schemes that make it possible to achieve a high level of user satisfaction with the recommended content. The satisfaction measurements rely on subjective user assessments [11] and on an automated evaluation of learning resources [6]. They can be estimated as an aggregation of user interest scores assigned to the recommended query responses or to the items recommended directly. Query processing will apply knowledge fusion methods such as combinations of recommendations, ex-post assessments of retrieved content and other methods [35].

3.1. The design of cognitive decision pilots for research recommenders

The application of recommenders does not make redundant the traditional value and role played by the intuition and experience of the decision maker. They remain relevant but can be enhanced by a computational system that ensures:

- a systematic survey and automated evaluation [6] of learning and research resources available on the platform,
- a personalized learning or research item acquisition and presentation (cf. [30], [46], and [47]).

The decision pilot can be regarded as a content recommender engine responsible for the automated assessment of items, formulating and solving problem (1)-(3) or (1),(4),(3) and gathering and representing the knowledge about the decision makers' preference structures based on cognitive behavioural analysis [33]. The degree of satisfaction of the decision maker with the recommendations thus generated supplies the information about the model quality and creates the basis for a supervised learning scheme.

The cognitive recommendation approach applied in decision pilots is based on the following key principles:

- All information resources available are explored to the maximum extent possible, observing user-defined temporal processing constraints.
- Inconsistent or contradictory content in the repository (e.g. article duplicates with mistakes in title or other metadata) can be disambiguated or judged on their usefulness before passing them to the recommended set.
- The recommendation can be performed incrementally in an open information space, i.e. in a situation when there is an inflow of items to the repository in real time or if real-time processing of visual or audio information is required.
- The elicitation of users' preferences is performed in real time as well.

Nervous, tired or irrational knowledge platform users may exhibit behaviour that leads to a chaotic choice of decisions, such that the conditions for terminating the decision-making process were never fulfilled. This may likely happen with some learners prior to exams, seeking information in a hurry etc. Therefore, in some situations, hurried or tired decision makers may especially need a quick and efficient decision aid. The recommenders whose design is based on automatic decision pilot principles will be able either to recommend deferring the learning strategy choice to a more suitable moment or generate a 'cautious' recommendation. By 'cautious' we mean the selection of an item or a set of items which conforms as much as possible to the decisions made previously by the user of the system user based on an individual cognitive decision model.

Based on previous experience with DSSs, we assume that mutually inconsistent or contradictory information found in the repository or received from the decision maker can be treated as a result of different cognitive processes. The identification of these processes enables a reconstruction, re-definition or averaging of faulty resources, converting them to useful material. Thus, the recommendation process avoids becoming loopy or inconsistent and the output generated in the end does not depend on the subjective sequence in which the additional information was processed.

Moreover, this assumption emphasizes the need to understand the human cognitive processes that accompany decision making. Incorrect or inconsistent statements are often caused by the shortcomings in the human perception of decision object features. A recommendation system based on an intelligent decision pilot is capable of tracing the learning processes on the platform, and the possible source of inconsistencies can be identified using a cognitive perception model.

Similarly, as in case of using price comparison engines and recommenders to support product selection in e-commerce systems, the quick changes of research or learning resources and tools available in a digital repository affect the recommendation process. In such situations, optimal stopping rules should be applied. The expected rise of information inflows from the web [39] to knowledge repositories will create a further need for more adequate cognitive recommendation mechanisms.

As an example of a cognitive extension of a decision approach, the procedure which measures the user's reply time in defining aspiration levels for learning in the well-known reference set method [36], then using the observation that for a certain group of users, the faster the reply is generated, the higher the probability of getting a correct reply. Another real-life cognitive observation that can be applied when designing decision engines for recommenders is the bicriteria trade-off hypothesis. This states that irrespective of the number of criteria used to make a choice, decision makers intuitively try to group them into two aggregated criteria then solve the bicriteria problem thus formulated. This hypothesis should be the subject of further psychometric investigation to identify the factors that influence the sequence of aggregation, relating them to feature perception and selection during recommendation processes.

3.2. Implementing cognitive content recommenders for a learning platform

Successful implementation of cognitive recommenders in learning and research have been reported e.g. in [25], [26], [43], [44]. Some of the solicited principles of recommendation systems capable of facilitating the use of a learning platform [19] and making it attractive for its users can be listed as follows:

- Irrespective of how advanced mathematical methods are used to process the underlying information and to generate the recommendation, the sophisticated procedures should not be directly visible to users (assumption of mathematical ignorance).
- The quality of automated recommendation should be enhanced by a collaborative systematic verification of the platform content, by its administrators and involving the users.
- A trust-credibility system should be designed and implemented (trust regarding users, credibility regarding the content items stored on the platform). Different trust and credibility models can be taken into account (cf. [9], [13], [20], [45]) focussing on those that allow for dynamic changes in trust and credibility measures in real time.
- A user-friendly recommendation assessment coupled with supervisory learning mechanisms should be built into the recommendation system. If necessary, the user should be able to redefine the recommendation with a dedicated intelligent agent so that the user’s preferences are satisfied to an optimal extent.

After a cold start and reaching a critical number of users, the recommendation algorithms will be gradually improved, and new cognitive decision making procedures and preference elicitation methods will be added. The use of additional preference information in the form of reference sets [36] and bicriteria trade-offs seems especially well suited to generating compromise recommendations and choosing satisfactory items. The recommendation will be supplemented by extensive visualization and guideline procedures, providing graphical and video object recommendations in an annotated form. Conversely, feature space methods that originate from image processing may be adapted for use with text and multimedia files [18]. In the mid-term future, human experts will only play the role of platform supervisors responsible for management issues and ordering missing items and data.

3.3 Search strategy recommendation as a cognitive process

A relevant issue that needs to be considered when designing a content recommendation system for a digital repository is the choice of a search-and-survey strategy to process queries capable of reviewing a very large number of feasible information sources. The survey planning approach, presented e.g. in [30], cannot be used in a dynamically changing environment with a very large number of potential knowledge sources, out of which only a quotient is explicitly known *ex-ante*. Also, a classical precision-and-recall assessment of responses to the query will fail for a number of reasons. In particular, the user will not be able to assess the results on his/her own and will be forced to delegate judgment on the quality of the reply and corresponding decisions to autonomous agents. A heuristic search-and-survey procedure can be designed making use of the *creative decision process* notion [36], where the user defines an initial subset of information sources according to some criteria, assigns them trust coefficients and activates the procedure that runs recursively at each information source, transforming them to autonomous agents with similar capabilities as the user. The design of such a procedure can be accomplished based on the creative decision process definition provided in [36].

Further development of the learning platform cognitive features may involve using specialized brain computer interfaces (BCIs, [41]) to elicit users' preferences and identify emotions in an efficient direct way. BCIs can also be helpful in adding the above-mentioned creativity-support-system functionalities to the knowledge repository [34]. Ultimately, sophisticated query design, extension, and recommendation procedures will allow the innovative learning platform [19] to develop towards a genuine GES [37].

4 Discussion and conclusions

Intelligent cognitive recommender systems constitute a new market and a social challenge. Their implementation horizon, from the current stage of development – item search and price comparison machines – seems more or less equivalent to the expected start of implementing a new class of innovative learning platforms exemplified by [19]. Cognitive recommendation software could create a new market trend, following the research trend evidenced in [40] and shown in Fig 1 below. The above trend, as well as the rise of multicriteria recommenders, will be enhanced by a rapid development of natural-language-based and multimedia search engines.

New decision-making concepts and methods make it possible to design intelligent autonomous recommendation systems able to make discoveries, anticipate the consequences of a decision made (cf. [38]) and enhance the quality of interaction with users. They are expected to be applied in an innovative knowledge repository coupled with a training platform developed within the ongoing EU Horizon 2020 research project MOVING [19] and in its future versions. Due to the growing importance of multimedia courses and other content, it is indispensable to combine visual information processing with recommendation and decision support algorithms, which is also a subject of the MOVING project.

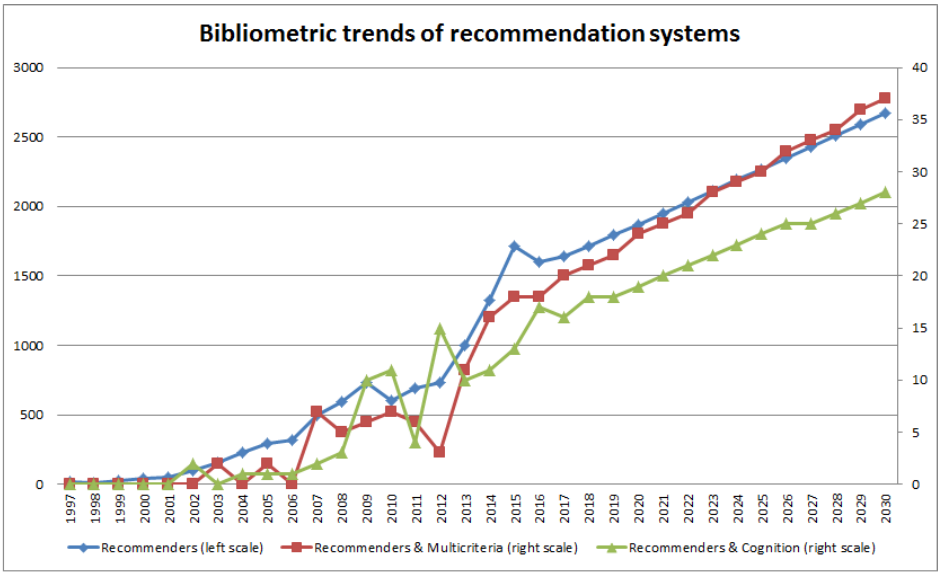

Fig. 1. Bibliometric trends based on Web of Science^{TM} (WoS) data from the period of 1997-2015 with ARIMA(2,1,0) forecasts until 2030. Left and right scales show the number of records in WoS for the respective queries.

The recommender design approach proposed in this paper extends the recommendation process to incremental learning of users' preferences, emotions, and satisfaction while using large heterogeneous knowledge repositories. Recommendation mechanisms are then adjusted to align to the present and expected cognitive state of a user. Thus the recommendation, user interaction with the repository and recommendation algorithm updates are combined in one anytime procedure with several levels of interaction. We claim that future recommenders will be endowed with a growing number of cognitive features and multicriteria decision algorithms. The latter will support increasingly autonomous and complex interaction of such systems with knowledge repository users.

The recommendation systems described here are assumed to work without any idealistic presumptions concerning the rational behaviour of users, and they are endowed with the capacity to check the consistency of a user's input and correct the choice. Together with content understanding capabilities, they will be able to propose optimal learning strategies based on multicriteria optimization algorithms when embedded in both mobile and stationary systems. One further potential application involves providing support to group learning where members are matched by recommendation mechanisms taking into account the expected compliance of users' attitudes towards learning and their psychological profiles. Such systems will be able to manage credibility and trust in group learning [37]. User reputation management mechanisms will be used to optimize the recommendations to the users to taking part in common learning or research. Recommendation will be enhanced by the activity of autonomous agents searching for statistical, patent, or bibliographic information. We expect that this principle will become the standard in future recommendation decision support systems, and its successful implementations will ensure the dominance of such systems on the intelligent recommender market.

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