On the Convergence of Intelligent Decision Aids

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ABSTRACT

On the one hand, users' decision making in today's web is supported in numerous ways, with mechanisms ranging from manual search over automated recommendation to intelligent advisors. The focus on algorithmic accuracy, however, is questioned more and more. On the other hand, although the boundaries between the mechanisms are blurred increasingly, research on user-related aspects is still conducted separately in each area. In this position paper, we present a research agenda for providing a more holistic solution, in which users are supported with the right decision aid at the right time depending on personal characteristics and situational needs.

KEYWORDS

Decision support, Human factors, Information filtering, Adaptive systems, Recommender systems, User experience, User modeling

1 PROBLEM STATEMENT

The spectrum of decision aids (DA) for users who are confronted with situations in which they can choose from large sets of alternatives ranges from manual search and filtering [21], over automated recommendation algorithms [48], to intelligent advisory components and conversational assistants [26]. All these mechanisms may help users in overcoming the information overload they would experience otherwise in today's web, and eventually, in making satisfying choices. Substantial research efforts have been made to improve the underlying methods on an individual basis, e.g., by using NLP in faceted filtering [17, 24] or deep learning for sequential recommendation [14, 47]. Yet, these algorithmic advances are seen more and more critically since less complex machine learning techniques often perform on a similar level of accuracy as modern neural networks [13], especially from a user perspective [41]. Overall, this perspective has gained importance in recent years, well illustrated by the numerous approaches from recommender research that improve user control or provide explanations [20, 29, 35, 55]. As a consequence, the DA proposed in various areas increasingly converge: As shown in Figure 1, interactive recommending approaches [e.g. 33, 37], dialog- or agent-based advisors [e.g. 31, 53], and conversational assistants [e.g. 6, 11], all are examples that come with the personalization capabilities of established recommendation methods, and thus, low interaction effort, but are more controllable and transparent, similar to manual exploration techniques.

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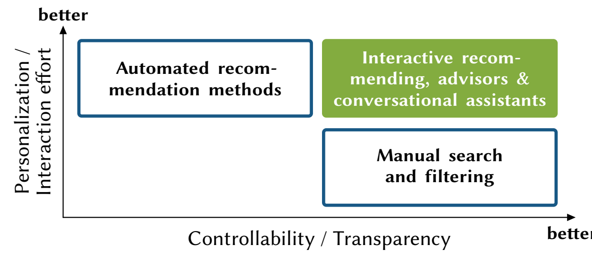

Figure 1: Mapping of different decision aids.

This is well in line with calls for a closer connection of the diametrically different mechanisms of (manual) search and filtering and (automated) recommendation [10, 18]. However, the approaches highlighted in Figure 1 have one problem in common: Though more interactive, they are considered as standalone solutions, mostly developed and evaluated separately. This neglects that in real-world applications (e.g. online shops, digital libraries), multiple DA are usually available, and it depends on the user's personal characteristics and situational needs, which method is currently the most suitable one. Until now, this problem has been addressed only at a very specific level, e.g., by combining selected interactive recommending techniques [39] or dialog-based advisors with filtering mechanisms [31]. We and others started to model interaction behavior when DA from two or more areas are available [30, 49, 58], but these are only first steps towards a holistic solution that adapts the presentation of DA to the current user. In this position paper, we discuss the challenges that still need to be overcome, and lay out a research agenda for always providing the right mechanisms from the full range of options that can assist users in decision making.

2 RESEARCH AGENDA

Taking recommender research as an example, it has been pointed out that the systems' interfaces should adapt to personal and situational characteristics [7], and become less dependent on behavioral data [16]. The effects, e.g., of domain knowledge or personality, on the desired level of control and usage of interactive features already have been investigated [27, 28, 42]. However, these works stop at the boundaries of this area, disregarding that the decision-making process, e.g., in online shopping, is usually much less straightforward than often anticipated under experimental conditions. In fact, users use (and switch between) several DA, each with a different impact [9, 25], before settling on a final choice [49, 58]. Thus, it is inevitable to take a broader perspective, first in future *evaluation* work: Again with respect to recommender systems (RS), it is worth noting that users' mental models often do not correspond to actual implementations, and are subject to large inter-individual differences [45]. To adequately design applications in which the recommender is only one of many components, we thus propose to

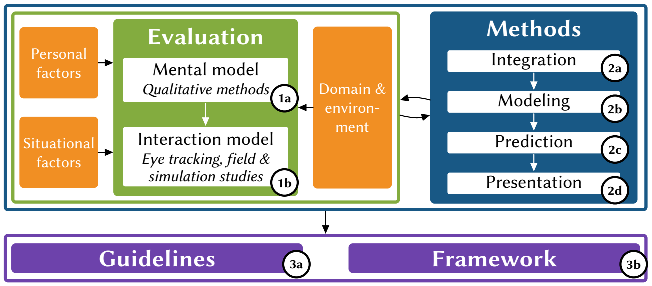

Figure 2: Our proposed research agenda.

first explore 1a) *mental models* also for these more complex cases (cf. Figure 2). Based on *qualitative methods* such as grounded theory [12], this will allow to better understand users who are not bound to a single DA. However, even with only a recommender, many paths may lead to the same goal [52]. Consequently, we propose further to conduct 1b) *user experiments* on the influence of user (e.g. demographics, cognitive style) and situation (e.g. task, device) also at this superordinate level. Only few works have yet explored such factors in relation to the tendencies to use different mechanisms [30, 49, 58]. But, the insights from objective behavioral data are limited, while questionnaires require self reflection disconnected from actual system usage, and, worse, often consumption or experience [36]. Thus, eye tracking or other methods to in situ measure the suitability of individual DA will be required to create a comprehensive formal *model of user interaction*. While *field studies* could ensure model validity under real-world conditions and capture temporal changes, it might also be necessary, in light of the ever-increasing design space, to come up with methods for *simulation studies* to investigate long-term user behavior. This particularly applies as domain and online environment likely are other mediating factors: Product type (search vs. experience) and category (streaming content or high-risk items such as hotels), together with the general impression of the application, may determine whether a user just goes with the first recommendation or needs support by an advisor.

Once more is known about perception of and interaction with environments in which multiple DA are available, it will be possible to work on specific *methods*: We propose to start by pursuing a closer 2a) *integration* of methods from all three areas identified as in Figure 1: While combinations of RS algorithms were made interactive, often through complex mechanisms [e.g. 5, 8, 38, 57], or (simple) search functionalities were added [e.g. 15, 34], only few works (cf. previous section) have yet extended existing DA and improved their interplay. Hence, there is a need to facilitate switching between components, without losing the progress made or raising any conflicts, e.g., due to filter settings that do not match the answer to a conversational assistant. In case natural language input is possible, e.g., in such a conversation, this will require specific modeling approaches [61]. Next, however, the 2b) *modeling* of the user can take place: Profiles that describe interaction behavior and preferences for certain assistants were presented long ago [50]. For RS, additional browsing data have also been considered [59, 62]. But, to offer a meaningful alternative to common RS profiles that only contain user-item preferences, it is crucial to consider users' hidden characteristics [32]. Recently, an attempt to create "holistic user profiles" has been made [43]. Together with the formal interaction model, this provides everything needed to determine which information to collect and how to store it in an adequate manner. However, since information on personality and context is usually not readily available, this might require developing techniques for implicit acquisition [1, 60] or for asking users explicitly [23, 54]. Either way, 2c) *prediction* will become possible: Again for RS, deep learning has shown success in predicting the likely next action based on past interaction sequences [51]. Thus, given the closer integration and the richer user modeling, it should also be an option to determine which of all available DA is currently most useful for the active user. Yet, self-reinforcing loops, constraining the user to certain interaction mechanisms, must be avoided [46]. For this reason, among others, it is finally important to explore the possibilities for the 2d) *presentation*: Earlier works on RS have shown, e.g., significant effects of presenting items or the entire interface in different ways [4, 19, 40, 44]. Whereas only behavioral data were considered in these cases, studying factors such as personality has a long tradition in user interface design [3]. This might turn out useful for an adaptive presentation of DA, especially for raising awareness of the mechanisms the system has predicted to be of relevance before, in a persuasive but unobtrusive manner: Explanations, currently used in RS mainly to explain item recommendations [55], but also perceived differently depending on user characteristics [22], could be used, e.g., to highlight the benefits of continuing the interaction with a specific DA. However, to account for factors such as the user's tendency to maximize, or his or her used device, a more active personalization of the entire component arrangement equally needs to be considered.

As illustrated in Figure 2, these four steps need of course to be interwoven with the evaluation described before, possibly causing updates to the formal interaction model. Then, however, we expect as outcomes of this user-centered process both insights and a set of specific methods that will enable us to come up with 3a) *guidelines* similar to the "recommender canvas" [56], which lists aspects to help specifically with the design of RS. This may provide support for practitioners and researchers at a superordinate level, to help design applications that integrate multiple intelligent DA. Another result could be a generic 3b) *framework* that, as done for enabling interactivity in non-interactive RS [2], allows to implement a layer on top of existing applications that automatically adapts the presentation of the (at most loosely connected) DA to the active user. This highlights again the difference of our planned work to others: Combining the benefits of existing approaches just to come up with "yet another interactive method" as shown in Figure 1 is not our goal, but instead, making these benefits, i.e. one DA or the other, available to the right user at the right time.

3 CONCLUSIONS

We wanted to bring attention to the problem that research on interactive, intelligent DA is often too narrow. We presented an agenda to overcome this problem, which is however neither exhaustive nor conclusive, in particular, with respect to the methods to use in certain steps. Nonetheless, we hope that it may help start a discussion about more holistic solutions, not restricted to a specific research area, but assisting users on a global level.

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