How does transparency of recommender systems influence the user experience?

Eva Noritsyna

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Abstract

Previous studies have shown that the perception of a recommender system can have varied effects on the measurable user experience. Research has shown that the transparency of a system can improve a person's trust in the system and the expected usefulness, and have a potential effect on usability of a system. However, transparency has also been reported to have negative effects on users' perception of the system. In this literature review, how transparency in recommender systems affects and influences user experience (UX) in terms of usability, trust and user expectations is evaluated. The findings conclude there being a causal relationship between transparency of a recommender system and its usability and user trust. However, user expectation is seen as an additional result of certain methods, in particular social influence, that could be utilized to achieve transparency.

Keywords: Recommender systems, transparency, user experience, recommendations, usability, trust, user expectations.

1 Introduction

The predictive power of recommender systems to produce personalized results is beneficial in numerous industries and has been emerging rapidly over the last two decades [3]; from recommending music that a user in particular might like to catering the news results specifically for them. Following the growing use of these systems in people's daily lives, there are also increasing concerns about the quality of user experience associated with them. As recommender systems are commonly used commercially, a criteria for their success is how popular their use is and how likely the users are to return. Therefore not only the algorithmic accuracy but also the user's trust and willingness to use the system is important.

Previous studies have shown that the perception of a recommender system can have varied effects on the measurable user experience. Users feel reluctant to enjoy the full benefits of such systems due to the privacy concerns related to them [22]. Others report machine recommendations as less appealing than those of their friends, despite being more accurate to their interests [14]. The interface of the system is a crucial factor of the user experience, impacting the ease of use and the perceived usefulness of the system [13]. Multiple focus areas have been identified as important for improving general end-user satisfaction, including the design of rating scales [2]. When well designed, these components decrease the initial user effort needed to get accustomed to the system which can be linked to better expectations.

Although substantial research is geared to optimising the accuracy of the predictions of recommender systems, various studies have found that users valued it less than factors such as an even balance of relevance and novelty of the results, which got the highest rating user-satisfaction wise[10]. Additionally, previous research has shown that the transparency of a system can improve a person's trust in the system and the expected usefulness, likely prompting the user to familiarize themselves with it. Transparency here refers to two categories; user-perceived transparency (justification) which comprises of explanations to the user of why a certain result might be recommended to them (eg. *"You might like **A** because you liked **B** and **C** and they are similar*), and objective transparency which comprises of explanations of how a recommender algorithm is operating and is defined as

> recommender revealing the actual mechanisms of the underlying algorithm [4]

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A limitation in this line of research is the quantifiability of user experience. Whilst one of the most common ways to measure it have been surveys, their drawback is lack of normalization between studies. Therefore, guidelines surrounding transparency in recommender systems are often based around the anecdotal commercial success of certain features [6].

Thus, an identifiable area of research that does not not have a widely adopted consensus is the extent to which transparency is important in measurable user experience of recommender engines. Transparency is considered to be part of a successful explanation [17] providing the reasoning behind recommendations and operations of the system [8]. It has been argued that too much transparency in a system can act as a obstacle to the general end user, and present limitations such as users attempting to "cheat" a system or raise even more confusion after providing seemingly arbitrary statistics (e.g. "22% similar to your tastes") [9]. On the other hand, insufficient transparency can worsen the user's expectation of the system by not providing enough credibility. This may act as a barrier to the functionality of the system, which is providing recommendations.

This literature study aims to evaluate how transparency in recommender systems affects and influences user experience (UX) in terms of usability, trust and user expectations and evaluate this trade-off, between transparency and functionality, in the context of these areas of user experience. Here, usability is defined as the ease of use of the system by the end-user. Trust is interpreted to be the level of trust the user has in the system, privacy-wise and recommendation-wise. This is relevant as if the user does not have a deep enough understanding of the system, they may not want to give up their personal information nor trust the recommendations they get out of the system to be accurate. Trust has been determinedly shown to be crucial for recommendations [5]. Lastly, expectation is defined as the user's perceived usefulness of the system. This is an important factor to consider as in the case that the user does not have the expectation of the system being useful for them, they are not likely to attempt employing the system, therefore the functionality of the system would be devalued.

In order to assess the trade-off, a variety of empirical findings categorized by these areas will be contrasted to reach a consensus regarding measurable influence of transparency. The methods used to achieve transparency will also be compared and contrasted in order to estimate the relatedness of the achieved results to the method.

The end-user considered in this literature review is a wide-range of demographics, without a strong technological background. This is specified as to avoid users considered in this study needing less transparency to understand the system.

2 Method

2.1 Search

The relevant material for this literature review has been gathered from the following online databases: ACM Digital Library, arxiv.org, Google Scholar and Scopus, by carrying out a methodical search on the pertinent keywords. These include but are not limited to: transparency, recommender systems, recommender engines, criteria of user experience, privacy concerns in recommender systems, transparency in algorithmic systems, explainable recommender system, explainable AI. Additionally, articles cited from the found articles were also checked.

2.2 Selection Criteria

The search results were filtered to find articles aimed to define the concepts of transparency in recommender systems as well as articles discussing the User Experience in the context of recommender systems and other explainable algorithmic systems. Greater attention was paid to empirical or survey studies aimed at determining the effect of changes to the system on the user experience.

2.3 Results

Paper	Empirical method	Transparency method	Usability/Trust/User-Expectation
[11]	Interviews and surveys	Textual Explanations	Usability (Usefulness, Convinience, Satisfaction)
[12]	Interviews, critical methods, surveys	Textual algorithmic explanations	Usability (satisfaction)
[13]	Behavioural log and questionnaire	Textual Explanations	Usability (satisfaction), User Expectation(perceived usefulness)
[4]	Surveys (pre and post use)	Textual and visual explanations	Usability (efficiency, effectiveness, satisfaction)
[18]	Post-use interviews	Visualisations	Usability (efficiency, effectiveness, satisfaction), Trust
[7]	Survey of 24 recommender systems	Analysis of of objective and user perceived transparency	Usability (satisfaction, usability), Trust
[8]	Post-use interviews	Focus on perception of transparency	Trust (confidence)
[19]	Analysis of reaction times, surveys	Textual algorithmic explanations	Trust (confidence, novelty)
[16]	Literature review	Textual explanations	UserExpectation, Trust (perceived confidence)
[23]	Online and offline user study	Sentiment analysis of user reviews	User Expectation
[21]	Designed recommendation framework	"Side-information embedded in textual user reviews"	User Expectation
[20]	Post-use self-report	Question-bank for evaluation transparency	User Expectation
[9]	Surveys	Three levels of textual explanations	User Expectation, Trust

Table 1:

2.4 Limitations

The generalised limitations of the research discussed in this literature review are the uses of surveying studies. There has been no consensus in normalising the relative ratings and answers, both qualitatively and quantitatively across studies. Moreover, the difference of scales and normalization techniques across examined articles results in inconsistent quantitative results. Therefore, the established trend in results has been highlighted from the majority of the studies, rather than the quantitative findings.

3 Discussion

3.1 Usability

In the results summarized in Table 1, usability has been discussed in various contexts such as the usefulness (effectiveness) of the system to the user, the convenience (efficiency) of using the system and the satisfaction of using the system. Usability is an important factor of continuance intention, meaning the likelihood of a user to want to reuse a system because if a system is difficult to use and doesn't provide satisfaction to a user, they are unlikely to return to it.

Shin argues that user-perceived transparency is the first step of the cognitive process that ultimately results in a higher level of "perceived value of usability" [11]. Whilst the judgement of transparency in the majority depends on the user, Shin and Parl [12] argue that this initial perception of how transparent a system is, which is increased by additional information about the justifications of the results, is a crucial factor of the usability, as well as trust and satisfaction, of the system that the user will perceive.

To explore the usability of a recommender systems, behavioural logs alongside questionnaires were the main source of measure of effectiveness [13]. Usability has been found to increase following provided explanations and thus increased transparency, in spite of "higher cognitive effort from the user" being necessary [4]. This may seem counter-intuitive, but can be used to highlight the importance of transparency for users, as they are willing to spend more time and cognitive effort in exchange for having a better justification of the recommendations. A tagcloud (word cloud of relevant tags) has had the best results in improving transparency and usability [4]. Moreover, a user-perceived transparency, instead of objective transparency has shown to have positive effect on the usability that users have reported in the final questionnaires.

Visualisations as a form of aid to recommendations systems have been evaluated by various studies [18]. By cross examining a variety of interactive recommendation system frameworks He, Parra and Verbert have identified how the main objectives, including transparency, of recommender systems can be approached. [7]. Efficiency and engagement, seen as parts of usability, have demonstrated improvements from having visualisations in all of the frameworks that have been evaluated for these. The time to complete tasks is shown to be shorter, whilst the average time of use of the system is longer. These findings can highlight that visualisations provide grounds for both, improved transparency and improved functionality rather than a trade-off. Fifteen frameworks conducted post-use user studies and found visual explanations practical in aiding users in comprehending why a particular result is being recommended to them as well as "relations of recommendations" and other "underlying data" [7]. Additionally, He, Parra and Verbert found that introducing recommender system visualisation has a positive impact on their perceived usefulness.

From considering the results in the context of usability, the conclusions that can be drawn are that transparency has a seemingly antecedent role in usability of a system [11] and presenting more information is favourable to achieving higher user-perceived transparency, especially in a visual format.

3.2 Trust

The hypothesis of whether not understanding a recommendation caused users to report lower liking and trust in the final recommendation has been examined through the means of surveying users based on multiple variations of a recommender system. Users were examined on "blind recommendations", which are those that they have not come across before, as well as "reminded recommendations", being results that they have encountered before. The findings support that "blind recommendations" cause not only less confidence from users, but also prove to generally be less liked [15]. Moreover, when providing "reminder recommendations" transparency was still reported as preferred.

Vitale and Tonkin [19] support these findings and extend them by using methods other than surveying (analysis of user consent and user experience) but also analysis of reaction time that it took every user to trust the system. The analysis of the empirical findings fully supported that a more transparent system allowed for a better user experience, in most of the six dimensions of user experience that were defined and considered in Vitale and Tonkin's study. The dimension that coincides with this review's measure of trust is novelty, as can be seen from Table 1. Vitale and Tonkin showed novelty to be rated much higher and consequently the trust to be significantly improved.

In spite of 86% of users who have answered a questionnaire expressing that having explanations in the recommender system improving their trust in the recommendations, a crucial point raised by Herlocker, Konstan and Riedl [8] is the fact that while explanations promote transparency and improvements in user experience, automated collaborative filtering systems, which represent a majority of recommender systems, pose a "black-box" problem in which it is extremely difficult to provide a simple explanation to the end user, with "extracting meaningful information" being the biggest challenge. Aside from worsening the quality of the explanations, using non-meaningful information as part of explanations can have detrimental effects on the perceived confidence in these recommendations of end users, making it less likely for them to want to use the system again[16].

Following on this issue, Verbert, Parra, Brusilovsky and Duval propose and evaluate the use of visualisations to achieve better transparency in results by combining distinct entities ("users, tags, recommender agents") [18]. Therefore, while a big part of recommender systems exhibit black-box behavior thus being difficult to extract relevant information for explanations, visualisations can often expose some underlying patterns providing the end-user with greater understanding of why some recommendations are made, even if implicitly. This is more beneficial and efficient in promoting trust in the system than non-meaningful or algorithmic explanations.

3.3 User Expectation

Sinha, Swearingen and Medhurst [13] have determined that expectations of the system are correlated to both the accuracy and novelty of the recommendations provided. However, these factors were not exclusively considered to be influential, as the more information was provided during all stages of use of the system, the better expectation the user had. In Sinha, Swearingen and Medhurst's study, the users reported better perceived usefulness of the system from having more information on the items they were being recommended (20% more), as well as what the recommendations were based on (10% more). Introducing additional descriptive information of the content [23], [1], is a common way of improving the transparency of the system which has a direct influence on perceived usefulness of the system, most effectively done by the means of "neutral descriptive adjectives" extracted from user reviews [21]. An implication of this is the possibility that both transparency and the user expectation of the system get improved by introducing human reviews (and their extracts) of the content as justifications for certain recommendations. The mentioned concept of social influence on perceived usefulness was also reported by Sinha, as users reported better results when shown other people's reviews instead of solely system recommendations with explanations.

However, this can be contrasted against the finding that *"Is there anyone in my social network that has received a similar recommendation?"* is the lowest ranking question users perceived as useful knowledge when using a recommender system [20]. The implications of this contrast can be extended to users appreciating and ranking some social influence on their expectation as important, the proximity of the users whose reviews (or extracts) were examined has a much lower importance.

Additionally, questionnaire results from Verbert, Parra, Brusilovsky and Duval's research showed that users were certain in visualizations providing them with more insights into the list of items, and improved their perceived usefulness of the system, proving to be another method in achieving both better transparency and better user expectation. The question *"Do you think that providing agents parallel to real users is helpful to you"* had that largest variance of answers, suggesting real users, and thus social influence, by itself often already being useful enough in understanding recommendations.

By utilizing a UX model to examine the interaction of users with a recommender system, Shin's findings confirm the Expectation-Confirmation Theory (ECT) and further explore the concept of transparency influencing the confirmation step rather than the expectation step [11]. Consequently, Shin argues that UX methods to improve transparency can only have an effect on perceived usefulness of a system after some initial use of it, thus on the Confirmation step. Therefore, this implies that transparency of the system does not have a direct effect on the user expectation of the system.

4 Conclusion

This literature review was aimed to evaluate how transparency in recommender systems affects and influences user experience (UX) in terms of usability, trust and user expectations. The review has identified that transparency of a system is a precedent of the usability and a crucial factor of the user's trust in the results of the system, therefore seems to have a causal relationship. However, the study found that the user expectation doesn't seem to be influenced by transparency, but rather also improves by the same methods as those aimed to improve transparency of a system. These findings also provide insights into methods that are effective in introducing transparency, user expectation, and all their results into the system. These include having a social aspect in providing recommendations; referencing other users' reviews or their extracts and/or visualising recommendation data. The review has found that any additional information in recommendations is perceived positively or neutrally as long as it is presented as an explanation to improve user-perceived transparency rather than a technical explanation to improve objective transparency. This study adds to the growing body of research that indicates the importance of transparency in building of good recommender engines. In spite of its limitations, the literature review has gone some way towards enhancing the understanding of the effects of transparency on UX in particular. These findings call for further normalised empirical studies to obtain a more comprehensive view of these relationships.

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