Reinforcement Sensitivity and Engagement in Proactive Recommendations: Experimental Evidence

Laurens Rook, Adem Sabic and Markus Zanker

Abstract We drew on revised Reinforcement Sensitivity Theory to claim that users with an anxiety-related behavioral inhibition would experience proactively delivered recommendations as potential threats. Such users would display higher user engagement especially when they were interrupted by inaccurate (vs. accurate) recommendations, because they ruminate about them. This prediction was tested and confirmed in a controlled experiment that exposed participants to proactive recommendations on their smartphone. Results highlight the need to gain more knowledge on the neural correlates of anxiety, and to apply such insights to human–computer interaction design for recommender systems.

Keywords Behavioral inhibition · Fight-flight-freeze system · Recommendation delivery · Proactivity · Human–computer interaction

1 Introduction

Recommender systems (RS) are automated decision support tools designed to provide custom-made advice on items to facilitate people's navigation in large information spaces [1]. RS provide personalized suggestions based on presumed preferences and needs of a user and other people's behavior. They help people overcome information overload either by providing accurate recommendations on

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request or by delivering them proactively. In addition to making the most accurate predictions to a user, also alternative measures for recommendation quality such as novelty, diversity, and unexpectedness of recommended items are increasingly explored [2]. In the present study, we take a NeuroIS approach to RS [3] by drawing on revised Reinforcement Sensitivity Theory (RST), a biopsychological theory from cognitive neuroscience [4], to posit that users with sensitivity towards behavioral inhibition will experience unexpected proactive recommendations as potential threats, try to cope with them via error-related rumination, and that this will lead them to display higher user engagement under the right circumstances.

2 Theory

2.1 Reinforcement Sensitivity Theory and Prediction

Originally, RST [5] explained personality as grounded in a general behavioral inhibition system (a brain system related to anxiety triggered by novel stimuli) and a behavioral approach system (a brain system triggered by reward and non-punishment). Revised RST [4] split the behavioral inhibition system into primary anxiety (BIS-Anxiety) when someone is confronted with conflicting novel stimuli, and secondary anxiety initiated by fight-flight-freeze responses to fear (FFFS-Fear). Neurologically, such aversive behaviors are located in the hippocampus, partially mediated by the prefrontal and right inferior frontal anterior cingulate cortex, and right inferior frontal gyrus [6, 7]. Interestingly, in laboratory settings, people prone to BIS-Anxiety have been found to be more sensitive to goal-conflict (e.g., novel information not making sense from an appetitive-aversive point of view). They easily detect such errors, and usually invest cognitive effort in correcting them—turning into anxious ruminators whenever necessary. Consequently, people with BIS-Anxiety typically perform well in intellective tasks. They tend to excel in educational setting, and seem to flourish in intellectually demanding jobs—especially, when those people are above average in intelligence, and hold desk-based (vs. hazardous) positions in industry [8]. It should be emphasized that—however sparse the applications of RST on industrial and organizational psychology—especially the resolution of goal-conflict of people with BIS-Anxiety is regarded beneficial to workplace behavior, as it may facilitate problem solving at work [9].

Combining RS and revised RST literatures, we claim that proactive recommendations can be understood as novel and unexpected—but potentially threatening—stimuli, which users receive when browsing for information on their computer devices. RS may facilitate search activity in tune with individual preferences [1, 2] for people not qualified by primary anxiety, but trigger goal conflict in users high on BIS-Anxiety—especially when RS appear inaccurate, leading such users to anxiously ruminate to trace and correct the error—which, eventually, leads to higher user engagement. This novel prediction, inspired by prior work on neural correlates of technology acceptance [10], was put to the test in an experimentally controlled user study.

3 Method

3.1 Participants and Design

Participants from a Dutch university enrolled in an applied statistics course were randomly assigned to the experimental conditions of a Recommendation Accuracy (high, low) factorial design on User Engagement, to which BIS-Anxiety and FFFS-Fear scores were added as covariates. An initial sample of 156 participants (87 men and 69 women; *M* age = 21.17 years, SD = 1.49) completed the study, but excluded from analyses were the data of those (*N* = 25; 16.03%) who reportedly did not receive proactive recommendations while working on the experiment (see below). This resulted in a final sample of 131 participants (71 men and 60 women; *M* age = 21.21 years, SD = 1.49), which was used for the analyses reported below.

3.2 Materials and Procedure

Per email, participants were invited to take part in a study on responsible e-tourism. They first completed an online pre-survey assessing the BIS/BAS scales [11] (see below) and demographics. Next, they received instructions to download a smartphone application from the Google Play or Apple App Store, depending on their mobile operating system. In the application environment, participants were asked to find a way to travel from Delft, the Netherlands, to London, UK on a specified date to attend a major event and to find a place to stay during the event. Precisely 60 s after their first exploration of these tourism-related challenges, they began to receive proactive recommendations, depending on experimental condition (see below). On completion, participants received the link to an online post-survey assessing manipulation checks and user experiences with the application. Participants were debriefed in class as to the purposes of the study.

3.3 Measures

Manipulation of Recommendation Accuracy. To induce the recommendation accuracy manipulation, participants received five proactive recommendations that were either highly or marginally relevant. Participants in the high recommendation accuracy condition received RS directly useful for solving the issues of mode and means of travel and accommodation. Participants in the low recommendation accuracy condition received RS relevant for a stay in London, but too generic to solve the posed trip planning challenges.

Behavioral Inhibition System. The original BIS/BAS scales [11] and their Dutch translation [12] were used to measure individual differences in BIS-Anxiety and FFFS-Fear (following instructions by [13]):

BIS-Anxiety. Four items measured BIS-Anxiety: *Criticism or scolding hurts me quite a bit*, *I feel pretty worried or upset when I think or know somebody is angry at me*, *I feel worried when I think I have done poorly at something important*, and *I worry about making mistakes*, on a 4-point scale anchored at 1 (*very true for me*) and 4 (*very false for me*; Cronbach $\alpha = 0.71$).

FFFS-Fear. Three items measured FFFS-Fear: *Even if something bad is about to happen to me I rarely experience fear or nervousness* (reverse coded), *If I think something unpleasant is going to happen I usually get pretty worked up*, and *I have very few fears compared to my friends* (reverse coded), on a 4-point scale anchored at 1 (*very true for me*) and 4 (*very false for me*; Cronbach $\alpha = 0.57$), which occurs more often [14], and is accredited to the small number of items in the scale.

User Engagement. Engaged users do not submit minimal results, but invest reasonable energy in solving challenging tasks properly [15], also in computer-mediated settings [16]. Consistent with this, we operationalized user engagement in the present study as the total number of characters that a participant submitted as solution for the series of travel tasks they had worked on.

Manipulation Check. Four items were used to assess whether participants had experienced the accuracy of the recommendations they received in line with experimental conditions. Example items were: *The travel solutions I produced for the e-Tourism Challenge were of good quality* and *The recommended set of links for the e-Tourism Challenge enabled me to submit high-quality travel solutions* on a 7-point scale anchored at 1 (*not at all true for me*) and 7 (*very true for me*; Cronbach $\alpha = 0.83$).

4 Results

4.1 Manipulation Check

A linear regression analysis on the four items of the manipulation check for recommendation accuracy showed a significant main effect of low versus high recommendation accuracy, $\beta = 0.48$, $t(130) = 2.14$, $p < 0.04$, which indicated that participants indeed had experienced the quality of the proactive recommendations they received in line with the experimental condition they had been randomly assigned to. This confirmed that the manipulation had been effective.

4.2 Correlations

Table 1 shows the descriptive statistics and the bivariate correlations. Recommendation accuracy was not in itself significantly correlated with BIS-Anxiety and FFFS-Fear or with User Engagement. Consistent with prior studies, BIS-Anxiety and FFFS-Fear were significantly and positively correlated [13, 14, 17]. FFFS-Fear was significantly and negatively correlated with User Engagement.

4.3 User Engagement

We conducted a series of negative binomial regression analyses to explore the main effects of Recommendation Accuracy, BIS-Anxiety, FFFS-Fear, as well as their interactions, on User Engagement. The likelihood ratio for the full negative binomial model was $\chi^2(7) = 22.02$, $p < 0.01$, which showed that our model was significant. Negative binomial regression analysis revealed a significant interaction effect of Recommendation Accuracy and BIS-Anxiety on User Engagement; people high on BIS-Anxiety displayed more user engagement in the face of inaccurate (vs. accurate) recommendations. Further test of the simple interactions yielded a significant main effect of BIS-Anxiety on User Engagement when Recommendation Accuracy was low, Wald $\chi^2(1) = 1.00$, $p < 0.05$, but not when Recommendation Accuracy was high, Wald $\chi^2(1) = 1.00$, *ns* (see Fig. 1). Probing of a significant three-way interaction indicated that this interaction effect between Recommendation Accuracy and BIS-Anxiety existed only for people low on FFFS-Fear, Wald $\chi^2(1) = 1.00$, $p < 0.0001$, but not high on FFFS-Fear, Wald $\chi^2(1) = 0.00$, $p = 0.93$.

Table 1 The descriptive statistics and the bivariate correlations

	M	SD	1	2	3	4
1. Recommendation accuracy	0.52	0.5	–			
2. BIS-anxiety	11.45	2.31	0.08	–		
3. FFFS	8.08	1.69	0.08	0.36**	–	
4. User engagement	139.60	125.68	−0.09	−0.14	−0.17*	–

Note $N = 131$; *$p < 0.05$ level, **$p < 0.01$ level; two-tailed

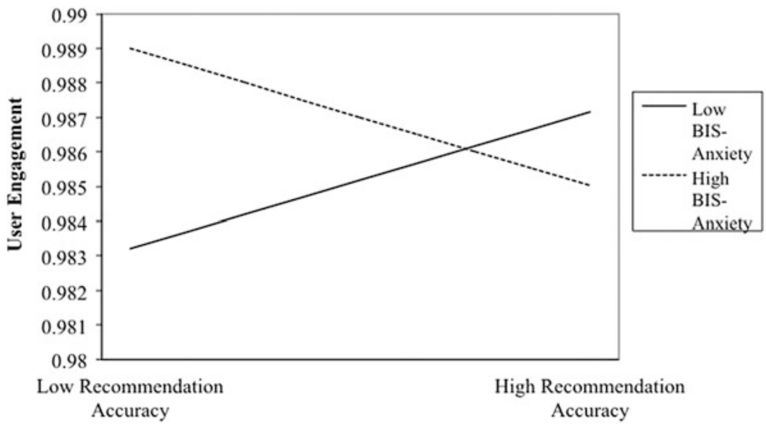

Fig. 1 Recommendation accuracy × BIS-anxiety on user engagement

5 Discussion and Conclusion

The present study reported first evidence that people high on BIS-Anxiety display higher levels of user engagement when exposed to inaccurate recommendations, because they, apparently, put more cognitive effort in finding and restoring inaccuracy errors. This confirms extant theorizing in RS that accuracy alone is not enough [18], and makes clear that consideration of alternative quality measures like novelty, diversity, and unexpectedness, indeed, holds major potential for yielding heightened user engagement [2]. Importantly, though, the key contribution of the present study lies in its recognition, derived from the neuroscience research framework of RST, that proactivity must be understood as trigger for constructive behavioral inhibition—that is, when RS are designed such that they refrain from invoking fear. Given the documented association between behavioral inhibition and the stress hormone cortisol—also in disruptive human–computer interactions [19]—it makes perfect sense for future study in this direction to propose a NeuroIS [20] research agenda aimed at explicitly establishing this cortisol-inhibition linkage also for proactive RS. In addition, traditional electroencephalography (EEG) procedures for testing cortisol-inhibition linkages [7] could in future work be adapted to our experimental paradigm to explore when proactivity turns into a stressor invoking fear rather than anxiety. For anxiety-prone users, this would make the difference between vigilant versus unproductive, unhealthy or no user engagement, whatsoever. In conclusion, the present study, therefore, shows the viability of adopting a human–computer interaction perspective on RS in general, and on taking a neurobiological perspective to the study of proactive recommender systems in particular.

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