Go With the Flow: Effects of Transparency and User Control on Targeted Advertising Using Flow Charts

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ABSTRACT

Targeted advertising reaches users based on various traits, such as demographics or behavior. However, users are often reluctant to accept ads. We hypothesise that users are more open to targeted advertising if they can inspect, control and thereby understand the process of ad selection. We conducted a between-subjects study (N=200) to investigate to what extent four key aspects of ads (*Quality, Behavioral Intention, Understanding and Attitude*) may be affected by transparency and user control using a flow chart. Our results indicate that positive effects of flow charts reported from other domains may also be applicable to advertising: Using these to provide transparency together with user control is found to have more positive effects on domain-specific quality measures than established, text-based approaches and using either of the techniques in isolation. The paper concludes with recommendations for practitioners aiming to improve user response to ads.

CCS Concepts

•**Human-centered computing** → *Visualization design and evaluation methods;*

Keywords

Targeted advertising; transparency; user control; flow chart

1. INTRODUCTION

Targeted advertising has become ubiquitous and companies such as Google, Facebook and Yahoo have built their own targeted advertising platforms to attract users. As a result, U.S. Internet ad revenue has reached a historic high, augmenting to $11.4 billion in Q1 2014 and $13.3 billion in Q1 2015 – a 16 percent increase in a single year [2]. By enabling companies to offer ads to users that match their preferences, targeted advertising is considered more effective than traditional advertising [7]. Yet, users often have a negative attitude towards this form of advertising due to privacy concerns and irrelevant content [11, 38]. For instance, users may fear the non-consensual use of their data by third parties or feel irritated by the same flight ad being shown repeatedly despite having already completed the booking.

To address these issues, some ad publishers such as Facebook, explains the ad selection. In addition, it allows users to control the collection and usage of data or to give feedback about the relevancy of ads [1]. However, we find that these publishers explain ads using solely text and only describe what kind of user is targeted by the shown ad. Therefore, it is still difficult for users to understand how the ad is selected specifically for them. Moreover, many users still lack confidence to control the data, be it due to limited understanding or due to bad user interfaces [13]. Also, the common predefined feedback options for ads ("ad covers this page" and "stop seeing ads") in Google and Facebook may not be sufficient to configure ads effectively. For a user to not be "banner blindness" [10] and for the ad to be well-placed and effective, a high degree of **transparency (TR)** and **user control (UC)** over the ad selection may be required [32]. To use these means effectively, it is important to understand how each of them can be supported and how their configuration, in combination or alone, can effect the success of targeted advertising.

Previous work in the domain of programming has found flow charts to be effective for presenting complex structural relationships of cause and effect, being superior to text-only explanations especially for inexperienced users [14]. As a result, the question arises as to whether a flow chart may not also be suitable for displaying the effects of user traits and preferences onto ad selection, thus achieving a higher degree of user-acceptance than current text-based approaches.

To investigate, we employed a design-based approach to explore how supporting TR and UC with the help of a flow chart can influence a list of key success measures. For this, a Facebook web app (PARIS-Ad) was developed that shows ads matching a played movie trailer and the user profile (age, gender, ad preference, and personality). The PARIS-Ad has two features: *the explanation of ad selection* as TR (transparency) and *the control of ad selection using a user profile* as UC (user control). While users edit their profile, a flow chart visualises the factors and processes influencing ad selection. This allows users to understand the impact of their profile on the ad selection process and thereby increases their acceptance of ads.

Based on a widely used evaluation framework for recommender systems [34], we measure the success of ads based

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on four key aspects:

- ***Perceived Quality*** of the ad (interest match, context match, attractiveness and annoyance)
- ***Behavioral Intention*** of the user (willingness to click, purchase and see)
- ***Understanding*** of the ad selection
- ***User Attitude*** towards the ad (satisfaction, acceptance confidence and trust)

We use these to evaluate the impact of of TR and UC on users' acceptance and engagement with targeted ads, displayed while watching a movie trailer. We hypothesize that quality and effectiveness of ads can be increased by empowering users to explore and steer the selection process. To verify our assumption, we investigate the impact of TR and UC on these key aspects as follows:

- ***Quality***: Can TR and UC support the user's *Perceived Quality* of an ad?
- ***Behavioral Intention***: Can TR and UC influence positively a user's behavior towards an ad?
- ***Understanding***: Can TR and UC allow users to understand why and how a particular ad is selected?
- ***Attitude***: Can TR and UC positively influence the user's *Attitude* towards an ad?

Several past studies on user perception of targeted advertising have discussed the importance and benefits of having TR or UC [13, 32, 39]. However, to the best of our knowledge, no comprehensive research exists investigating their capability to improve targeted advertising. Further, established approaches, as used by Facebook [1], have so far not used interactive visualisations to implement TR and UC into targeted advertising, but merely text-based explanations. As a result, our work makes three contributions:

1. Our study presents the first implementation of flow charts into the domain of targeted advertising to illustrate cause and effect of user traits and preferences on ad selection. Our results indicate that the positive effects of this visualisation reported from other domains may also be applicable to that of targeted advertising, offering a new field of application and thus extending the validity and scope of previous findings.
2. With regards to previous work on user perception of targeted advertising [32], our study reveals the following new insights:
    - Providing transparency improves a user's *Behavioral Intention*
    - Providing user control improves a user's *Understanding* of the ad selection process
    - Providing both transparency and user control improves the aspects *Quality*, *Behavioral Intention*, and *Understanding*
    - The aspect of *Attitude* does not appear to be affected by either approach.
3. Vendor Relationship Management (VRM) promotes the use of TR and UC to improve customer engagement with vendors [36]. In this regard our study may be seen as a proof of concept concerning the successful application of a subset of VRM principles to the domain of targeted advertising.

This paper is organized as follows: After an overview of related work, we introduce the design of the PARIS-Ad, followed by a description of our study and its results. We conclude with a discussion and practical advice.

2. BACKGROUND AND RELATED WORK

2.1 Targeted advertising

In order to make ads relevant and appealing to individual users, targeted advertising adapts to user traits, behavior and context [32] using two main approaches: Contextual advertising (CA) and Behavioral advertising (BA) [30]. CA shows relevant ads based on the content of the website users are viewing. A user who is reading a news article having the keyword "football" may for instance receive a football jersey ad. BA tracks user online behavior, such as visited websites and posted content, to predict user interests of ads. A user who liked the movie "Minions" on Facebook may for instance receive a Minions T-shirt ad. When comparing these forms of targeted advertising, BA has been found to be more effective than CA [44, 7] and less harmful to the perceived credibility and quality of a site [12]. However, targeted advertising often collects user data and tracks user behavior. This may be perceived as a violation of privacy, especially when it does not show the scope of collection, use, and privacy conditions [28]. Previous research has focused on improving the four key aspects of targeted advertising success as follows:

A first aspect is *Perceived Quality* of the ad, including its *attractiveness*, *interest match* and *context match*. Malheiros et al. [30] showed that increasing personalization at a certain level could increase ad attractiveness. Cramer et al. [12] noted that avoiding confusion is important for quality perception. In fact, if the context match is too high, the perceived ad quality of an ad may actually be decreased [12].

A second aspect is *Behavioral Intention* of the user, including *willingness to click, purchase and see*. Previous work has shown that Click-Through Rate (CTR) of an ad can be increased substantially by properly segmenting users for ad delivery [43]. Other authors [20] use a segmentation technique that categorizes users by psychological traits affecting buying behavior as a basis to personalize ad delivery. Yet, users generally have a negative attitude towards targeted advertising due to annoying content [18] and privacy concerns [45].

A third aspect is *Understanding* of the ad. Liu et al. [29] presented a browser-based tool named AdReveal to increase understanding of ads. It shows detailed measurements of the ads based on targeting mechanisms used by ad publishers.

A fourth aspect is user *Attitude* towards the ad, including *satisfaction, confidence and trust*. Richardson et al. [35] presented a model predicting the CTR for new ads to optimize ad selection. They found that by using this approach, user satisfaction with the ad service was increased. In addition, Goldsmith et al. [17] suggest that company trust and credibility have a significant impact on user *Attitude* towards the ad. Finally, Ur et al. [39] propose that acceptance can be increased by providing users with a certain degree of control.

In summary, previous work has tried to improve ad success using a range of techniques. However, the effects of TR and UC on the four key aspects have so far not been investigated.

2.2 Transparency and user control

In the domain of information visualisation, several researchers have focussed on making complex processes transparent with the help of flow charts: Crews et al. [14] used them to help novice programmers understand algorithms. They report an increase in confidence, reduction of errors and task completion times [14]. Similarly, Van Heel et al. [40] as well as Yue and Anderson [46] used flow charts effectively to present complex information flows, allowing users to diagnose and prevent workflow problems. Finally, Kennedy et al. [25] used a flow chart to illustrate the cause and effect of genotype alterations, allowing users to explore several "what-if" scenarios. In summary, flow charts have been found to be an effective tool for illustrating complex processes for users of all skill levels, increasing their engagement with and understanding of a topic. As a result, the question arises as to whether this type of visualisation may also be suitable to explain the process of ad selection based on the characteristics of a user's profile to likewise increase user engagement with and acceptance of displayed ads.

Many ad services on social networks leverage recommender techniques together with TR and UC to target users and improve their results [24]. For instance, the Facebook Ads page explains why one is seeing an ad and allows the configuring one's ad preferences. In addition to textual explanations, interactive visualizations have been deployed on top of recommender systems. These help users to understand the rationale behind recommendations and allow them to fine-tune parameters according to their needs. TalkExplorer [41] explains the provenance of recommendations and supports exploration and control by end users, increasing effectiveness of item selection. TasteWeight [9] and PeerChooser [33] allow users to inspect recommendations and change parameter weighting, resulting in increased accuracy. Others have shown positive effects of transparency on trust, agreement, satisfaction, and acceptance of EC recommendations [42].

To explain a recommendation, some systems [6, 23] visualize the user profile using a radial view. Similarly, System U [5] shows personality traits by using a Sunburst technique whereas Bogdanov et al. [8] use an icon-based visualization to represent user preferences for music – however, without explaining how these influence recommendations.

In contrast, PARIS-Ad provides exactly this type of insight into the recommendation process: it shows how the user profile is used and in which order the various characteristics affect ad selection. By doing so, the PARIS-Ad incorporates principles of Vendor Relationship Management (VRM) [36], which suggests to add TR and UC to targeted advertising to increase ad success. Adding TR and UC as a possible means to alleviate *privacy concerns* has already been discussed [30, 39], as well as the encouragement of users to share data [28]. However, most advertising platforms still provide ineffective user control [4, 39]. This prompts an exploration of how we may effectively combine transparency and user control using graphical visualisation in order to improve user response to targeted advertising. To the best of our knowledge, the effects of adding TR and UC on ad recommendation have not been researched yet.

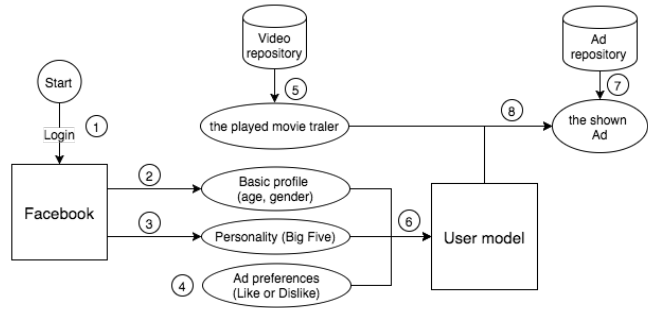

Figure 1: Workflow of generating personalized ads.

3. DESIGN OF PROTOTYPE

We implemented an app (PARIS-Ad) that shows ads relevant to a movie trailer being played on the page by using the user's Facebook profile. In addition to age, gender and ad preference – which are the most essential elements for targeted advertising – targeting by personality traits is also an effective way of reaching users [19]. Therefore, PARIS-Ad shows targeted ads based on user age, gender, ad preference, and personality. To support transparency, the app also shows the user data employed for the targeting as well as an explanation of how an ad was selected. To support user control, the app enables users to select ad categories and modify their profiles.

Figure 1 shows how PARIS-Ad generates the targeted ad. First, users log in to the web app with their Facebook accounts. The app then obtains age and gender from their Facebook profile (step 2) as well as posts of their timeline. These are used to derive personality traits in step 3. We employed the IBM Watson Personality Insights service [3] to calculate the score for each of the Big Five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. In step 4, the "Like" and "Dislike" buttons allow users to indicate their ad preferences. In step 5, the played movie trailer is retrieved to get ads relevant to the current context. Step 6 shows the user model built from the output of steps 2, 3 and 4. In step 8, the trailer (step 5) and user model (step 6) are used to select a specific ad from the set of ads (step 7).

To test the effect of ads, previous work has employed varying repository sizes: Farahat et al. [16] explore the effectiveness of targeted advertising by evaluating brand-related searches and clickthrough rates of 18 advertising campaigns on nine front pages. Cramer [12] used 45 ads to explore the effect of ad quality on perceived site quality, whereas Goldstein et al. [18] employed a pool of 144 ads to "analyze features that relate to annoyingness" of ads. Using these numbers as an orientation, we chose a pool size of 70. This way we hope to reduce possible effects of varying ad content on user response while providing a reasonable degree of choice from seven categories: Clothes, Food, Movie, Automotive, Toy, Travel, and Cosmetics. We then assigned meta data to these based on context and user profile [15].

Figure 2 shows the user interface for transparency and user control. An ad appears in part (a) and the "Like" (green) and "Dislike" (red) buttons enable user feedback.

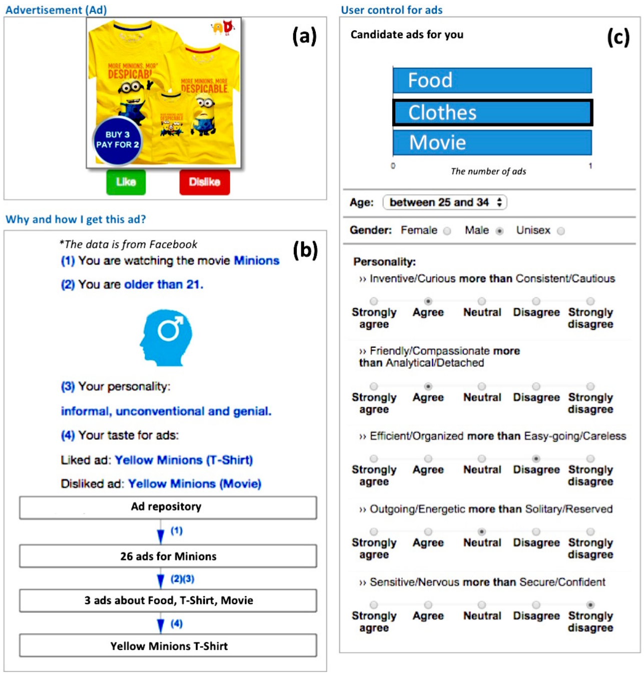

Figure 2: PARIS-Ad screenshot. a): ad window. b): the upper part shows the user profile including watched movie trailer, age range, gender, personality and ad preferences; the flow chart shows the process of ad selection. c): the control panel to switch categories of candidate ads and edit the user profile.

When clicking "Dislike", another ad will be shown. Part (b) explains why a particular ad is shown (transparency) while part (c) supports user control. Figure 2 (b) also shows the provenance of the user profile (Facebook), watched movie (Minions), age range (older than 21), personality (informal, unconventional and genial) generated by the IBM Watson API [3], and recently liked/disliked ads.

3.1 Transparency

Below the personality description and recent responses, a flow chart (Figure 2 (b)) explains the ad selection process: After the repository has been filtered for context-matching ads (step 1), step 2 and step 3 show the ad categories relevant to the user's age, gender and personality. A final step (step 4) then considers recently "liked" ads by the user to make a final decision. If multiple matches are found, a random ad is selected from these.

3.2 User control

By editing their profile in the right part of the interface (c), users can directly observe the changes in the generated personality on the left (b) together with its effects on the ad selection process in the flow chart. The personality profile allows the definition of age, gender and personality, with the latter being based on five statements provided by the IBM Watson Personality Insights service, assessed using a five-point Likert scale [22]. In addition, users can interact with the bar chart at the top to highlight a certain category which they specifically would like to see ads for.

4. EVALUATION METHOD

We conducted a between-subjects study on Amazon Mechanical Turk (MTurk) with 200 subjects. Compensation was $1 per study and average study completion time was around 11 minutes. Data was collected as follows: we used the user-centric evaluation framework of Pu and Chen [34] and designed a questionnaire to consider the four key aspects of targeted advertisement we defined earlier. In addition, we evaluated willingness to click and purchase as a basis for assessing ad effectiveness, as proposed by Lavrakas [27]. We thus created four post-study questionnaires QueA, QueB, QueC and QueD to assess the effect of TR and UC in different conditions.

All questionnaires asked about age and gender while providing space for comments. Further, each questionnaire included 11 common statements (see Table 2) for assessing ads with regards to the four key aspects: *Quality* (STM1-STM4), *Behavioral Intention* (STM5-STM7), *Understanding* (STM8) and *Attitude* (STM9-STM11). Subjects were asked to rate each statement using a five-point Likert scale.

In addition to the 11 common statements, questionnaires QueB, QueC and QueD had a set of specific statements and optional questions regarding users' perception of TR, UC and TR & UC combined. These specific statements were rated using the same five-point Likert scale. Mouse movement and clicks where recorded in a log.

4.1 Design

We conducted a between-subjects study to see whether and which of the four key aspects (*Quality*, *Behavioral Intention*, *Understanding* and *Attitude*), represented by the 11 statements (Tab. 2), are affected by transparency (TR), user control (UC) and a combination of both. The conditions were as follows:

- **Condition 1 (C1):** This is the base condition. Ads were shown without TR and UC (No-TR & No-UC): the page displays the video player and the ad window as shown in Figure 2 (a).
- **Condition 2 (C2):** Ads were shown with transparency only (TR & No-UC): the page displays the video player, the ad window, and explanations as to why the ad was selected (Fig. 2 (a)(b)) .
- **Condition 3 (C3):** Ads were displayed with user control (No-TR & UC): the page shows the video player, the ad window, and a user control panel (Fig. 2 (a)(c)).
- **Condition 4 (C4):** Ads were displayed with transparency and user control (TR & UC): the page shows the video player, the ad window, explanations of the selected ad, and a user control panel (Fig. 2 (a)(b)(c)).

Before starting the study, each subject was given a brief introduction, explaining the PARIS-Ad system. Subjects could only participate in one condition. Following this, subjects were asked to log in to the app with their Facebook accounts. After this the movie trailer started to play and ads were shown to subjects. During the trailer, subjects could rate the ads by clicking the "Like" or "Dislike" buttons. After watching the trailer, subjects were presented the corresponding questionnaire. Playback controls were disabled to ensure that subjects were exposed to ads for a minimum of four minutes before answering the statements.

Group	*Age range*	*Mean age, SD*	*Gender (F)*
C1	20-67	34.5, 10.1	62%, 38%
C2	20-62	34.0, 10.0	64%, 36%
C3	20-69	35.5, 10.6	60%, 40%
C4	20-63	33.6, 10.1	62%, 38%

Table 1: Subject demographics in four conditions.

STM1: The ads shown to me matched my interest.

STM2: The ads shown to me matched the context.

STM3: The ads shown to me are attractive.

STM4: The ads shown annoy me.

STM5: I would like to click the shown ads.

STM6: I would like to consume the products shown in the ads.

STM7: I would like to see the ads shown in this way in the future.

STM8: I understand why I get this ad.

STM9: Overall, I am satisfied with the ads service.

STM10: I am confident I will accept the ads shown to me.

STM11: The shown ads can be trusted.

Table 2: The 11 statements shown in QueA, QueB, QueC, and QueD.

4.2 Subjects

Each condition had 50 users (n=200 total, 198 valid, as two subjects participated in two studies). Age and gender were equally distributed among the groups (Tab. 1).

5. RESULTS

To analyze the responses, we translated the Likert scale as follows: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree. This was the same for all statements except STM 4, which is negated.

5.1 Responses to Common Statements

As the data was not normally distributed (Shapiro-Wilk, df=50, $p<.05$), we chose the Kruskal-Wallis test over the ANOVA and Dunn's test for the post-hoc, between-subjects pairwise comparisons. The results are as follows:

5.1.1 Quality

STM1 (interest match): The Kruskal-Wallis test showed an effect of configuration type on interest match (H=14.49, df=3, p=.002). While C3 and C4 tend to affect this aspect positively, Dunn's test revealed that differences are only statistically significant between C1 (median: 3) and C4 (median: 4), (p=.001). This suggests C4 to be the preferable approach for improving interest matching.

STM2 (context match): The Kruskal-Wallis test showed no effect of configuration on context match. This aspect was rated equally positive among conditions (median: 4).

STM3 (attractiveness): The Kruskal-Wallis test revealed no effect of configuration type on ad attractiveness. However, both C3 and C4 tend to be slightly higher rated (median: 4) than C1 (median: 3) and C2 (median: 3.5). Thus, C3 and C4 may be considered preferable for increasing ad attractiveness.

STM4 (annoyance): The Kruskal-Wallis test showed no effect of configuration type on ad annoyance. Ads were rated neutrally in C1, with a tendency of C2, C3, and C4 being rated positively (median: 4).

5.1.2 Behavioral Intention

STM5 (willingness to click ads): The Kruskal-Wallis test showed an effect of configuration type on click intention (H=11.42, df=3, p=.01). C4 tends to affect this aspect positively (median: 4), but a Dunn test revealed that differences are only statistically in comparison to C1 (median: 2.5), p=.014. This indicates that C4 is preferable over C1 for increasing a user's willingness to click ads, with a trend of C4 being the most favorable condition of all.

STM6 (willingness to purchase products in the ads): The Kruskal-Wallis test showed no effect of configuration type on purchase intention. This aspect was rated neutral (median: 3) in all four conditions.

STM7 (willingness to see ads shown in the current way): The Kruskal-Wallis test indicated an effect of configuration type (H=11.74, df=3, p=.008). Both C2 and C4 tend to affect this aspect positively: Dunn's test revealed that differences are statistically significant between C1 (median: 3) and C4 (median: 4), (p=.018), and between C1 (median: 3) and C2 (median: 4), (p=.030). This suggests C4 and C2 to be the preferable for improving this aspect.

5.1.3 Understanding

STM8 (Understanding of ads): The Kruskal-Wallis test showed an effect of configuration type on the understanding of ads (H=13.68, df=3, p=.003). C2, C3 and C4 tend to affect this aspect positively. Dunn's test revealed that differences are statistically significant between C1 (median: 3) and C4 (median: 4), (p=.009) and between C1 (median: 3) and C3 (median: 4), (p=.010). This suggests that C4 and C3 are the preferable configurations for improving a user's understanding of ads.

5.1.4 Attitude

STM9 (Satisfaction with an ad service): The Kruskal-Wallis test indicated no effect of configuration type on satisfaction. This aspect was rated equally high in all four conditions (median: 4).

STM10 (Confidence in accepting ads): The Kruskal-Wallis test showed no effect of configuration type on acceptance confidence. This aspect was rated neutral (median: 3) in all four conditions.

STM11 (Trust in ads): The Kruskal-Wallis test indicated no effect of configuration type on trust. However, the results indicate a trend for C2 to affect this aspect rather positively (median: 4) when compared to the other condi-

Config.	Quality	BI	Und.	Atti.
C1 (No-TR & No-UC)				
C2 (TR & No-UC)		*		
C3 (No-TR & UC)			*	
C4 (TR & UC)	*	*	*	

Table 3: Positive impact of each configuration (Config.) on the four key aspects *Quality* of the ad, *Behavioral Intention* (BI) of the user, *Understanding* of the ad (Und.) and a user's *Attitude* towards the ad (Atti.), marked by "*". The combination of TR & UC appears to be the most versatile approach.

tions. This suggests C2 to be potentially more suitable for increasing a user's trust in ads than the other conditions.

5.2 Responses to specific statements

In addition to the 11 statements, we explored subjects' opinions regarding the concepts of TR, UC and TR & UC by asking them to rate the specific statements of QueB and QueC and QueD. In summary, subjects tended to agree that the availability of transparency affected most aspects positively (QueB, median:4), similar to user control (QueC, median: 4). Equally, users tended to agree that TR & UC in combination affected most aspects positively (QueC, median: 4), apart from alleviating privacy issues and trust, where users showed a neutral opinion (median:3.25). Evaluating users' general comments, we found that they perceived the configurability of the ad selection process positively, but that they also uttered critical voices concerning privacy.

5.3 Log file data

Sixty-one percent of subjects in C4 and 48% of subjects in C3 clicked at least one ad, compared to 21% of subjects in C2 and 32% of subjects in C1. Eighty-four percent of subjects configured their user profiles in both C3 and C4. Specifically, 43% of subjects in C4 and 36% of subjects in C3 configured age range, 8% (C4) and 10% (C3) configured gender, and 82% (C4) and 84% (C3) configured their personality.

6. DISCUSSION

We discuss the effects of each configuration on the four key aspects of targeted advertising. Table 3 shows the most effective configuration for each aspect in brief.

6.1 Quality

The data indicates that using TR & UC (C4) leads to a higher *interests match* for the presented ads. However, using each of the components in isolation does not affect this aspect. Conditions C2, C3, and C4 appear to invoke a higher perceived *context match* for the ads, implying that TR and UC, regardless of constellation, may be equally suited to improve this aspect. The data also reveals that neither TR nor UC seem to affect the visual *attractiveness* and overall *annoyance* of ads. All in all, the results suggest that by combining TR & UC (C4), we can increase the relevance of ads and therefore their quality in the eye of the user.

6.2 Behavioral intention

The questionnaire and log file evaluation show that the combination of TR and UC results in an increase of *willingness to click* ads. This is supported by the work of [35], who attribute a high level of CTR to ads that are well-matched. With regards to the *willingness to purchase*, UC only appears to have a minor effect whereas the usage of solely TR does not seem to affect this aspect at all. This may be explained by the notion that purchase behavior is often influenced by cultural, personal, psychological and motivational factors [37] on which TR and UC have little effect. Here, Kacen et al. [21] have shown that mainly individual cultural difference influence impulsive purchasing behavior and that users often purchase those brands to which they are emotionally attached [31]. The results also show that subjects were *willing to see* an explanation detailing why the ad is selected together with the actual ad (C2 and C4). In addition, the log file data suggests that users liked to configure ads, suggesting a high impact of UC on user engagement.

Overall, the combination of TR & UC (C4) appears to be the best approach for improving *Behavioral Intention*. According to our findings, this configuration has positive influences on the *willingness to click* and *willingness to see*.

6.3 Understanding

The results suggest that both TR & UC (C4) and No-TR & UC (C3) allow subjects to understand why and how a particular ad is selected. It seems that user control has a stronger impact than providing static insight using TR, making it a key component for improving this aspect.

6.4 Attitude

Although we did not see a statistically significant effect of configuration on a user's *Attitude* towards ads, the responses to the specific statements in Que2 suggest that subjects tend to regard TR as a means to increase trust. In terms of increasing the acceptance confidence, all four configurations were rated neutral, meaning TR and UC both have little impact on this aspect.

Regarding the increase of trust in ads, using solely TR & No-UC (C2) seems to have a positive effect. However, the *Attitude* towards ads decreased when combined with UC. Users may surmise that by providing more data via user control, the application may be collecting private data. As privacy concerns are a major factor [42], such a suspicion can certainly reduce their trust. This may be exacerbated by showing the results of the Big Five character trait classification, potentially evoking a feeling of being spied on, as mentioned by one user in the general comments. This may offset the expected increased satisfaction resulting from the increased interest match of ads [35]. It seems that acceptance and trust are mainly influenced by company credibility and company trust [17]. However, user's attitudes towards targeted advertising are complex and context-dependent [39], complicating the definition of a possible cause for this behavior. It seems that influencing users' *Attitude* towards ads is part of a process that is not affected by ad-hoc control and insight. Rather, this may happen on a more emotional level and may be part of a long-term relationship between the user and a company, requiring a completely different approach.

7. CONCLUSION AND FUTURE WORK

Our work has evaluated the impact of transparency and user control – as proposed by the VRM project [36] – on the four key aspects of targeted advertising: *Quality*, *Behavioral Intention*, *Understanding* and *Attitude*. To do so, we evaluated the qualitative feedback of 200 participants in a between-subjects study. We found that while providing transparency can improve a user's *Behavioral Intention* and while providing user control can increase a user's *Understanding* of the ad selection process, the most successful approach is the combination of the two techniques. This way, we could simultaneously improve aspects of *Quality*, *Behavioral Intention*, and *Understanding* (Tab. 3). However, user *Attitude* towards advertising could not be improved using either approach. As a result, our work may be seen as a proof of concept of the ideas provided by the VRM project.

Compared to previous work [13, 32, 39], we could show the added value that can be gained from incorporating TR and UC into targeted advertising. In contrast to current text-based explanations [1], we allowed users to edit their personal profile and preference with the result of their choices directly visible in a flow chart. This way, users had a high degree of control and transparency, being able to graphically inspect why a certain ad had been selected. Following the improved results achieved with providing interactive control over this visualisation, the data suggests that the positive effects of flow charts reported for illustrating and manipulating processes in the domain of programming [14] or genetics [25] may also be applicable to the domain of targeted advertising. Thus, our study provides a proof of concept of the expandability of this type of visualisation to this field.

Using our results as a guide, ad publishers may gauge the trade-off between using either transparency and/or user control to increase the effectiveness of ads. For example, in order to increase a user's *Behavioral Intention*, providing solely transparency may suffice. However, to increase the ad's *Perceived Quality*, our results indicate that publishers would need to combine transparency and user control. Therefore, the benefit of including these in targeted advertising is double edged: Whereas the success of the served ad can potentially be increased, the cost of placing the ad together with the space required for providing transparency and user control may outweigh the benefits and has to be considered carefully. While this may not be feasible to incorporate into the ad space available on news sites, it may be more appropriate for different content types such as online games or online video portals, where content diversity is lower. Here, engagement with these controls could be introduced as a "quid-pro-quo" deal for accessing content.

As a result, future work will focus on reducing the space required for transparency and user control by investigating different layout options and by reducing the amount of settings and features necessary in these components to achieve the desired positive effects. Further, as our implementation does not include privacy inspection and configuration (which may impact user attitude toward ads), future work will incorporate this feature to investigate its interaction with and possible benefits to transparency and user control.

7.1 Limitations

Studies conducted via MTurk may suffer from inattentive or "spamming" users [26]. We aimed to address this problem by only choosing users with a minimum lifetime approval rate of 80%. While the sample size of 200 should lower the potential impact of possible rogue users, this issue needs to be considered when interpreting the results. Another limitation is the set size of our ad pool. Although previous work has successfully measured the effects of ads on user perception with smaller sets [18, 12], it is likely that a larger data set may increase the appropriateness and perceived quality of ads beyond the values reported in this paper.

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