Online Daters' Willingness to Use Recommender Technology for Mate Selection Decisions

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ABSTRACT

Online and mobile dating services often offer recommendation systems to facilitate decision making for their users. These recommendation systems take the form of *decision aids* that narrow down the size of the dating pool, or *delegated agents* that select optimal matches on behalf of users. An experiment examined three kinds of factors that influence daters to rely on such recommenders when selecting dates: (a) selection task factors (e.g., number of available daters in the pool and number of information attributes on a profile), (b) daters' personality (e.g., need for cognition), and (c) daters' pre-existing trust in recommender technology. The results reveal that daters were willing to use a decision aid under all circumstances, but that their intent to use a delegated agent was dependent on the size of the choice set and levels of technological trust. This effect was further moderated by personality, such that daters who had a higher need for cognition displayed greater willingness to use a recommender system when facing larger choice sets, compared to those low in need for cognition. This study provides insight into when users are willing to rely on different kinds of recommendation systems for decisions in online dating contexts.

CCS CONCEPTS

• **Human-centered computing→ Human computer interaction** → HCI design and evaluation methods→ User studies; Laboratory experiments

KEYWORDS

Social recommender systems, human-computer interaction, user interfaces, decision aids

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1 INTRODUCTION

Recommender algorithms help humans make decisions in a variety of contexts, including how to maximize productivity in the workplace, which stocks to buy on Wall Street, even which criminals to arrest [14]. Another place that recommender algorithms have inserted themselves is into the very "human" context of romantic love. Dating websites and mobile applications (apps) that claim to provide users with a technological advantage over decisions of the heart have now become a mainstay of the romantic landscape. Even Facebook recently entered the online dating industry by launching a new service they call Dating that "will use a unique algorithm to match you with potential dates, based on 'dating preferences, things in common, and mutual friends.'" [28]

As 15% of the American adult population reports using some online or mobile dating platform [35], the ubiquity of technology in romance suggests that people should be accepting of algorithmic recommenders. But an important question still remains: Under what circumstances do people accept aid from a recommender when searching for potential romantic partners?

In current information systems research, there is a lack of investigation into the "human side" of recommender systems—that is, users' perceptions and motivations for adoption of recommender technology. This is despite the fact that many researchers have noted that a better understanding of human decision making behavior and user experience would strengthen the design of recommender systems [5]. With this concern in mind, we examine how (1) properties of the selection task, (2) users' personality and (3) users' attitudes towards algorithmic technology affect their intentions to use recommender systems in the context of online dating.

2 BACKGROUND

The recent interest in recommender systems and online dating has been driven by the recognition that while recommender technology may not change users' romantic preferences, it does fundamentally change the process of mate selection and relationship initiation [9]. Dating systems vary in kinds of recommendation technology they offer users: Websites like the industry standard Match.com offer *decision aids* that help users whittle down the immense dating pool into a more manageable number of profiles. While decision aids act as a filter, *delegated agent* recommenders found in sites like eHarmony and mobile apps like Only and the European-based Once app provide daters a single optimal match once a day [see 17, 19].

Decision aids and delegated agent recommenders reflect varying amounts of technological involvement in users' decision making: Users who opt for a delegated agent recommender are granting more control over mate selection to technology, compared to those who opt for a decision aid. Uncovering the specific factors that determine when daters are likely to use a decision aid versus a delegated agent recommender system to facilitate their romantic decision making is the purpose of this work.

2.1 Selection Task Difficulty

One of the oft-touted advantages of online dating is the increased number of potential partners available to users. However, this increased variety can complicate the choice task, leading to *choice overload* "in which the complexity of the decision problem faced by an individual exceeds the individual's cognitive resources" [4]. Dating is a series of choices that are made within a social context, and these choices are still subject to many of the same issues as other decisions. Thus we rely on previous work on choice overload to predict that as choice task difficulty increases, decisions also become more difficult, which increases the likelihood of a dater relying on a recommender tool to aid in mate selection. In this study we examine two factors that increase choice task difficulty by creating overload: choice set size and information attributes.

2.1.1 Choice Set Size. Several experiments in the decision making literature consistently indicate that increasing the *assortment size of the choice set* during a decision task increases the effort required to make a choice, such that the benefit provided by greater variety may not offset the energy that individuals must expend to evaluate each additional option [e.g., 1, 4, 15, 26, 30]. One study of recommender systems and overload in the context of movie selection found that increasing the number of recommended options in a choice set did increase perceived variation for people, but did not necessarily boost their overall decision making satisfaction [1]. This result clearly illustrates the aforementioned tradeoff underlying increasing set size—though we may often enjoy the variety of a larger assortment, more options increase the difficulty of the choice.

One of the earliest studies [26] that examined varying choice set size in online dating found that daters preferred choice sets containing roughly 20-50 profiles and anticipated feeling overloaded and more frustrated by larger choice sets. In a more recent experiment, D'Angelo and Toma [6] instructed participants to choose a potential date from a set of either 4 or 24 profiles, and then asked one week later if they were satisfied with their initial choice or if they would like to change their selections. Daters choosing from the larger profile choice set were less satisfied with their choices and more likely to change their choices, suggesting that choice set size affected people's decision making response.

Elsewhere, Chiou and colleagues [24, 39, 40] predicted that the larger the pool of potential dating partners, the worse the final decision along two dimensions: (1) the "goodness of match," defined as the difference between the attributes of a preferred partner and attributes of the chosen partner, and (2) "selectivity," defined as the ability to devote attention to the daters who more closely fit their previously-indicated mate preferences. The authors reasoned that increasing options within the choice set should make mate selection more difficult by leading to less mindful information processing and reduced ability to weed out "poor" matches. Results revealed a linear trend across choice sets of 30, 60, or 90 profiles, with participants making decisions in the large choice set conditions reporting lower goodness of match scores and lower selectivity when compared to either the moderate or small choice conditions [40]. From these results, it was concluded that increased assortment size led daters to deviate more from the preferences they declared before they began looking for dates. Although one could argue that such deviations actually indicate better decisions (i.e., daters changed their preferences to match available daters in the pool), increasing choice sets still produced an observable effect on decision making behavior.

This review demonstrates that increased profile choice set size affects perceptions of the difficulty of the selection task in online dating (e.g., choice overload), and that increasing selection task difficulty also produces effects such as decreased decision making satisfaction and greater deviation from initial preferences. Thus, an important question is whether increasing choice set size will also increase daters' intent to use a recommender algorithm to help with mate selection as the task becomes more difficult.

2.1.2 Profile Information Attributes. Another factor that may increase the perceived difficulty of the choice task is the number of *information attributes* along which a dater is described (e.g., their demographics, hobbies, etc.). The more attributes displayed in a dating profile increase the complexity of the choice since comparisons among daters require contrasting the options across more attributes, thus increasing cognitive effort. The presence of multiple dimensions on which to compare potential partners may also render selection more difficult as the options become more similar [26]. The number of information attributes contained in profiles also represents a key design difference across popular dating platforms—for example, Tinder's relatively sparse amount of attributes per profile versus OkCupid's more extensive set of attributes per profile. We hypothesize that more information attributes displayed on a profile complicates the mate selection task and should lead to an increased willingness to rely on recommender algorithms in online dating.

2.2 User Personality: Adaptive Decision Making & Need for Cognition

The literature also suggests that daters' personal characteristics might influence their perceptions of recommender systems. Specifically, we predict that people's *adaptive decision-making behavior*—which refers to one's ability to employ multiple strategies to make an optimal decision based on the environment [31]—may affect recommender adoption. Because adaptive decision making depends on individuals' overall "cognitive development, experience, and more formal training and education", we focus on users' *need for cognition* (NFC) [2, 3] as a personality variable shown to be positively correlated with strategic adaptive decision making behavior. Indeed users' personality characteristics have been shown to affect their use of different recommender interfaces [21].

How might NFC be associated with adaptive decision making in the current context? Research in decision making suggests that online daters with higher NFC should be *more likely* than their low NFC counterparts to use a diversity of strategies, which should include recommender systems. Using a recommender to reduce options allows daters to engage in more explicit comparison of remaining profiles. Thus literature suggests that as the selection task gets more difficult, higher NFC individuals should exhibit a greater willingness to adopt recommender technology, reflecting their tendency toward adaptive behavior [27, 31]. In contrast, those with low NFC are less likely to exhibit adaptive decision making because they strive to expend as little effort as possible.

However, other findings point to an alternative relationship between daters' NFC and their adoption of recommender systems in online dating. As reviewed above, Lee and Chiou [25] found that high NFC daters were willing to search through more profiles than low NFC daters. Unlike the decision making research, these results suggest that high NFC daters may prefer the challenge of profile comparisons making them *less likely* to use an algorithm compared to low NFC daters who would prefer the recommender to help them select a date.

In this way, high NFC daters function as decision "maximizers" who will spend the effort to find the best possible option, as opposed to low NFC "satisficers" who simply find an option that fulfills basic criteria [34]. Interestingly, a study [21] examining if differences in cognitive decision style affected peoples' satisfaction with various recommender tools: Maximizers and satisficers did not display many differences in their satisfaction with different kinds of recommender interfaces (e.g., Top-N, sort, etc.). In this study, however, choice sets were held constant at 80 options—it remains to be seen whether increasing the difficulty of the choice interacts with cognitive decision style to affect reactions to recommenders.

Given this ambiguity across different literatures, the present study examines how daters' NFC is related to their intent to use recommender systems for mate selection as the number of options and attributes in each profile both increase.

2.3 Attitude toward Technology: Trust in Recommenders

The final factor predicted to affect people's use of recommenders for online dating is their *trust in recommenders.* Theoretical models of human-to-machine trust often divide the trust construct into two categories: *post facto* and *a priori* trust.

Users develop *post facto* trust after interacting with or otherwise observing the recommender system. Post facto trust is therefore founded upon people's exchanges with the algorithm, akin to what [29] calls *history-based* trust. Notably, most existing information systems and recommender system studies have focused almost exclusively on users' post facto attitudes and how they affect user experience or subsequent adoption of recommender tools [e.g., 7,19, 23].

In contrast, *a priori trust* suggests that people often approach recommender technology with some general level of trust. That is, they do not enter into interactions with recommendation algorithms as "blank slates"—instead, users often have some pre-existing attitude toward technology that may influence their future intentions to use it. Those few theorists who define users' *a priori trust* in machines have noted it consists of mostly positive impressions of technology as being very authoritative, objective, highly accurate, and extremely credible [7, 36]. What we call *a priori* trust has also been termed *dispositional trust* [29], *trust expectancy* [25], and *trusting propensity* [21]; all of these terms share a conceptual reference to those attitudes, impressions, or expectations that users bring with them into a first encounter, prior to any experience with the recommender.

Clearly, these two classifications of human-machine trust develop in very different ways. Users rely on direct observation with an algorithm to form post facto trust, while a priori trust is "ultimately an affective response" [25]. However, most existing experiments often instruct participants to interact with a recommender system and then look at the effects of this interaction on user attitudes or behavior. This has led to a focus on users' post facto trust, and a failure to consider how a priori trust affects users' willingness or resistance to adopt recommender systems at the outset.

To better understand how *a priori* human-machine trust functions, the current study examines how two dimensions of *a priori* trust in recommender algorithms influence subsequent intentions to use them: (1) *a priori cognitive trust* defined as users "rational expectations" of the system's integrity, ability, and reliability; (2) *a priori emotional trust* defined as "the extent to which one feels secure or comfortable" about relying on the system [16]. This study tests whether users' *a priori* cognitive and emotional trust in recommenders affects their desire to use them in the context of online dating.

3. PRESENT STUDY

The present study tested how increasing *choice set size* and varying *profile information attributes* affected people's intentions to use recommender systems before actually interacting with them. After learning how many daters they would be choosing from and how much information they could obtain about each dater through their profile (see design, below), participants were asked how willing they would be to use a decision aid or a delegated agent.

While both recommenders were described as applying daters' pre-specified criteria to the dating pool, the *decision aid* was described to participants as a system that assisted mate selection by reducing the number of available profiles in half. The *delegated agent* was described as a system that optimized mate selection by selecting the single, most compatible partner from the entire pool. This was a strong manipulation (reducing by half vs. reducing to one), but it is reasonable in the context of online dating systems given that some major platforms reduce the choice pool to a single match, at least for a given time period (e.g., eHarmony, Once).

3.1 Experimental Design

Our study followed a 4 x 2 between subjects design. For our manipulation of *choice set size*, we relied on previous work that indicated that the average number of profiles a dater would review in a single sitting was 170 [39]. Therefore, we created four choice set conditions with considerable range of options that were both below and above average: 4, 64, 204, 804.

For the *profile information attributes* factor, the high information condition (modeled on Match.com profiles) contained 13 attributes of the dater (e.g., photo, screenname, age, gender, location, height, about me section); the low information condition, modeled on Tinder profiles, only five attributes were displayed. Figure 1 displays samples of experimental stimuli.

3.2 Hypotheses and Research Questions

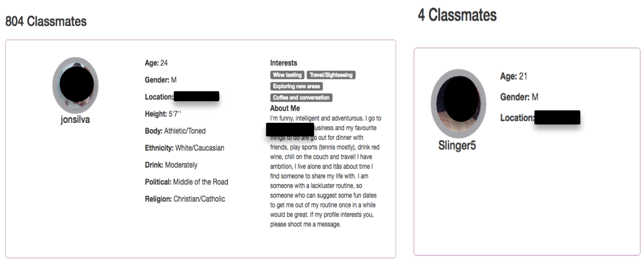

Figure 1. Example stimulus profiles featuring main experimental manipulations.

We first predict that elements that increase the perceived difficulty of the mate selection task are related to intentions to use both types of recommender systems:

H1: Increasing assortment in choice set size increases daters' intentions to use (a) decision aid and (b) delegated agent recommender systems for online dating.

H2: Increasing information attributes in the profile increases daters' intentions to use (a) decision aid and (b) delegated agent recommender systems for online dating.

As competing predictions exist regarding the effect of need for cognition on the relationship between selection task and recommender system adoption, we ask a research question:

RQ1: Does individual need for cognition moderate the relationship between choice task difficulty and daters' intentions to use recommender systems for online dating?

Lastly, we advanced hypotheses regarding *a priori* trust:

H3: Users' *a priori* (a) emotional trust and (b) cognitive trust are positively related to intentions to use recommender systems for online dating.

H4: Users' *a priori* trust in recommendation algorithms moderates the relationship between choice task difficulty on willingness to use recommender systems, such that as mate selection increases in difficulty, (a) greater emotional trust and (b) cognitive trust combine to produce greater reliance on online dating recommenders.

4 METHOD

4.1 Sample

A sample of 129 participants (M_{age} = 20.35, *SD* = 2.13; 76% female) was recruited from a Midwestern university and compensated with class credit. Beyond convenience, college students are an appropriate population from which to sample, as 18-24 year olds represent the largest demographic group of American online daters, with usage up to 27% in 2016, from just 10% in 2013 [35]. Participants indicated their experience with online dating using a scale of 1 = strongly disagree to 7 = strongly agree: "I feel totally comfortable with online dating," "I am very experienced with online dating," "I am familiar with how online dating works" (α = .71, *M* = 4.01, *SD* = 1.32).

4.2 Profile Stimuli

Our team content analyzed 150 publicly available online dating profiles from a variety of websites and apps (PlentyofFish, Match.com, OkCupid, Tinder, etc.) and used this information to create the experimental stimuli. While stimuli profiles varied in content, care was taken to ensure consistency across self-description word count (e.g., 70-80 words), age (range 19-25), and profile photos (e.g., no full body shots). Stimuli profile attractiveness was controlled by carefully regulating the way in which profiles were displayed in the ClassMate website. First, photos were judged for overall attractiveness by a group of outside raters on a scale of 1 = "not at all attractive" to 10 "very attractive". A group of seven male judges rated female stimuli photos, *M* = 6.32, *SD* = 1.03. A group of 10 female judges rated male stimuli photos, *M* = 4.44, *SD* = 1.00. Using these ratings, a script was created so that a profile of average attractiveness would be displayed, followed by alternating profiles at one standard deviation above and below the average. Thus attractiveness was balanced across choice set conditions.

4.3 Procedure

Participants were told that the purpose of the study was to test a new website called ClassMate.com that was being developed specifically for college-aged singles. They were told that ClassMate was being tested at universities across the country and that their campus was selected as a test site; in actuality, this was a cover story. Procedures were approved by the university's institutional review board.

Participants began by creating a profile and were told that it would be shown to others enrolled in the study. They completed a pretest that asked for their desired preferences in a dating partner using 14 specific traits [37], and the *need for cognition* measure, *M* = 4.46, *SD* = 0.65, α = .83 [3]. This stage was done at home so that they could spend as much time as they desired on their profiles.

Participants came to the lab for the next stage and were told that their main task was to give their opinions about the "Selective Tracking and Relationship Test," or START tool, that was being developed for use in ClassMate. Participants watched a short video that explained the two versions of the START

Table 1. Correlation among study variables

Variable	1	2	3	4	5	6	7	8	9
1. Profile Set									
2. Information Attributes	-.05								
3. Perception of Overload	.59**	.05							
4. Need for Cognition	.05	.08	-.03						
5. Emotional Trust	-.007	-.03	.01	-.04					
6. Cognitive Trust	-.13	.02	-.07	-.08	.55**				
7. Intent to Use Decision Aid	-.06	.02	-.01	-.05	.51**	.47**			
8. Intent to Use Delegated Agent	.18*	-.06	.27**	-.01	.41**	.28**	.32**		
9. Online Dating Experience	-.07	-.07	.007	-.15	.39**	.33**	.28**	.25**	
10. Sex	-.19*	.04	-.016	.04	-.10	-.13	-.16	-.06	0.09

Notes. N = 129. * p< .05. **p < .01.

recommender that were being tested. As noted above, the *decision aid* recommender was described as a tool that applied users' mate selection preferences to reduce the dating pool by eliminating 50% of the options, leaving a more narrowed choice set from which daters could choose. The second variation was the *delegated agent* recommender, which would make the decision on behalf of the user by selecting the single, most compatible person from all available daters within the ClassMate network by applying their preferences.

After receiving explanations about the different variations of recommender tools, participants were randomly assigned to experimental conditions described above and given up to 5 minutes to familiarize themselves with the profiles and website interface. They were told they could use the ClassMate site more extensively after they completed the posttest questionnaire.

The posttest began with checks on the manipulations of selection task difficulty, which we operationalized as perceptions of *choice overload.* We used two items adapted from [15], "I think the number of daters in the ClassMate network is…" 1 = far too little, 7 = far too many; "I wish the dating pool contained ___ people" 1 = many fewer, 7 = many more, M = 2.70, SD = 0.79.

Because participants did not directly engage with either form of recommender, their measures of trust were based solely on their initial impressions of the algorithm. To assess *a priori emotional trust,* we adapted 3 items [19] that used a 1 = strongly disagree to 7 = strongly agree scale (e.g., "I feel comfortable relying on START for my romantic matching decisions"), M = 4.41, SD = 1.26, α = .92. For *a priori cognitive trust,* we adapted 5 items [19] (e.g., "START seems to have good knowledge about the daters"), M = 5.15, SD = 0.74, α = .93.

Participants indicated their *intentions to adopt the decision aid* on a 1 = strongly disagree to 7 = strongly agree scale (e.g., "I am willing to use START as a tool that suggests to me a number of potential partners from which I can choose"), M= 5.42, SD = 1.02, α = .91, and *intentions to adopt the delegated agent* ("I intend to let START choose my best romantic match on my behalf"), M = 3.82, SD = 1.52, α = .93. Behavioral intent is an important factor measured in both the Technology Acceptance Model [7] and the Theory of Planned Behavior [10], the latter of which was adapted for the current study, following [19]. To avoid order effects, the presentation of these two behavioral intention scales was randomized in the posttest.

Participants were debriefed and asked whether they suspected the purpose of the study or any of the manipulations. Two who said they were suspicious of the experimental procedures were excluded from inclusion in the final sample.

5. RESULTS

An ANOVA was used to examine whether our manipulations affected perceived selection task difficulty (e.g., perceptions of overload). As expected, the choice set size variable produced increasing perceptions of overload, F (3, 121) = 23.68, p < .001 (Table 2). The interaction between the factors was not significant, F (3, 121) = 1.41, p = .24, nor was the main effect for information attributes on perceptions of overload, F (1, 121) = 1.60, p = .21. In sum, only the choice set size manipulation contributed to participants' selection task experience.

5.1 Effects of Selection Task Elements on Intentions to Use Recommender Systems

Did the manipulations of choice set size affect willingness to use recommender systems? A linear contrast analysis [32] was used to test the predicted relationship between increasing choice set size and willingness to use recommender systems in H1. Regarding willingness to use a decision aid, the result was not significant, F (1, 125) = 0.42, p = .52; however, the contrast was significant for willingness to use a delegated agent, F (1, 125) = 3.96, p = .049 (see Table 2). In summary H1a was not supported; data were consistent with H1b.

There was no effect of information attributes on willingness to use a decision aid, F (1, 127) = 0.47, p = .50, or for on intentions to use a delegated agent, F (1, 127) = .06, p = .80. These data failed to support H2a and H2b.

These initial results helped us to refine our analytic strategy: Given the results of the manipulation check and lack of support for H2, the information attributes variable was dropped from subsequent analyses, as it did not affect participants' perception of the online dating selection task. Furthermore, the results of H1 clearly indicated that choice set size produced an effect on intentions to use a delegated agent, but not on intent to use a decision aid (nor were there any interaction effects). Therefore, in examining the moderating effects of need for cognition (RQ1) and effects of *a priori* trust (H3, H4), we included users' intent to use a delegated agent, and excluded intent to use a decision aid.

Table 2. Means and Standard Deviations for Profile Set Size Conditions on Perceptions of Overload and Intent to Use Recommenders

Choice Set Condition	Perceptions of Overload (*M, SD*)	Intent to Use Decision Aid (*M, SD*)	Intent to Use Delegated Agent (*M, SD*)
4 profiles	2.15 (0.71)	5.46 (0.98)	3.45 (1.61)
64 profiles	2.50 (0.77)	5.54 (0.76)	3.54 (1.37)
204 profiles	2.79 (0.58)	5.42 (0.90)	3.84 (1.37)
804 profiles	3.22 (0.57)	5.34 (1.16)	4.13 (1.48)

5.2 Users' Need for Cognition

Conditional process modeling [12] was used to test the moderation detailed in RQ2. Analyses were performed in SPSS version 25 using the PROCESS macro; this allowed us to analyze the effect of choice set size (X) on participants' willingness to use the SMART algorithm (Y) as a function of their NFC (M), using 10,000 resamples and controlling for age and online dating experience as covariates. Because our independent variable contained four categories, PROCESS created three dummy variables (D_1, D_2, D_3). We selected indicator coding based on the pattern of means uncovered in H1. Specifically, we used the 4-profile condition as the reference group, which resulted in ($D_1 = D_2 = D_3 = 0$); D_1 coded the 64-profile condition ($D_1 = 1$, $D_2 = D_3 = 0$); D_2 coded the 204-profile condition ($D_1 = D_3 = 0$, $D_2 = 1$); and D_3 coded the 804-profile condition ($D_1 = D_2 = 0$, $D_3 = 1$).

Following the analytic procedure outlined by [13], we first tested the unconstrained model, which was significant, $F(5, 123) = 2.96$, $p = .015$. The subsequent test of the increase in R^2 when the moderation effect of NFC was added to the model was also significant, $\Delta R^2 = .06$, $F(3, 119) = 2.77$, $p = .04$. Thus, with respect to RQ1 the effect of the number of profiles on participants' willingness to use the algorithm depends on their NFC (Table 3).

To probe this effect, we used the simple slope procedure at values of NFC's average (4.47), one standard deviation below (3.83) and one standard deviation above (5.11). As seen in Figure 2, we find that among those at or below the mean in NFC, choice set size did not seem to influence intentions to use the delegated agent. Increasing choice set size only influenced those who were high in NFC to use the recommender for mate selection tasks, $\Delta R^2 = .09$, $F(3, 119) = 4.15$, $p = .01$, suggesting that those higher in NFC may use the algorithm as a form of adaptive behavior.

Table 3. Regression of profile set condition on intent to use the delegated agent for mate selection when need for cognition is the moderator

	b	*SE*	*t*	*p*	*LLCI*	*ULCI*
Constant	4.26	1.58	2.70	.01	1.14	7.38
Sex	-0.22	0.33	-0.69	.49	-0.87	0.42
Online Dating Experience	0.33	0.11	3.04	.001	0.11	0.54
Need for Cognition	-0.42	0.33	-1.25	.21	-1.08	0.24
D_1	-2.27	4.89	-0.47	.64	-11.95	7.40
D_2	1.18	2.65	0.45	.66	-4.06	6.43
D_3	-4.29	2.04	-2.10	.04	-8.34	-0.25
D_1xNFC	0.47	1.10	0.42	.67	-1.72	2.65
D_2xNFC	-0.24	0.59	-0.40	.69	-.141	0.94
D_3xNFC	1.09	0.45	2.43	.02	0.20	1.98

Note. D = dummy variables using indicator coding, *b* = unstandardized coefficients, *SE* = standard error, LLCI and ULCI = 95% confidence intervals.

5.3 A Priori Trust in Algorithms

To examine predictions regarding *a priori* trust, we again used the SPSS PROCESS macro. We began by testing the relationship between choice sets and intention to use a delegated agent recommender, as a function of emotional trust (H4a). Examination of the moderating effect began with a formal test of significance for ΔR^2, which was not significant $F(3, 119) = 1.39$, $p = .25$. However there was a significant association between *a priori* emotional trust and intent to use the delegated agent that supported H3a, $b = 0.35$, $SE = 0.15$, $t = 2.36$, $p = .02$.

Our test of H4b revealed that the formal test of ΔR^2 was not significant, $F(3, 119) = 0.62$, $p = .60$, suggesting no interaction of cognitive trust and choice set size on intent to use a delegated agent recommender. A significant positive association between users' cognitive trust and willingness to use the delegated agent obtained, $b = 0.78$, $SD = 0.11$, $t = 2.58$, $p = .01$, supporting H3b.

6. DISCUSSION

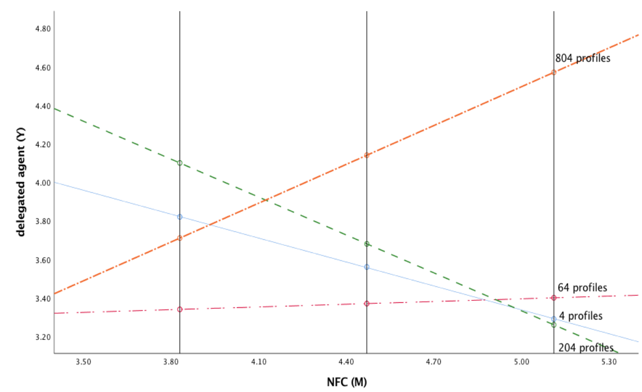

Figure 2. Visualization of the interaction between profile set conditions and need for cognition.

The current study examined how choice set size and profile attributes affected daters' intent to use two types of recommender systems. We find that within an online dating context, and before ever interacting with a system, most users are comfortable ceding some control to a decision aid recommender to streamline their mate selection. The surprising lack of effect of choice set size or information attributes for decision aids suggests that people have faith in using a recommender tool to filter out the bottom half of their pool, perhaps because they perceive that they still maintain some control over their final choice.

Daters are more discerning, however, when it comes to delegated agent recommenders, and intended to use them only when they perceived a difficult selection task with a large amount of options. This is perhaps not surprising given how much control participants had to give to the delegated agent, essentially reducing their dating pool to one person. This suggests there is a threshold for when decision making becomes so difficult that a delegated agent becomes attractive.

Although our explanation regarding differential nature of control across decision aid and delegated agent conditions are speculative, they parallel previous work in both online dating partner selection [38] and recommender systems, more generally [1, 21, 22]. The concept of control is an important factor to consider when studying user adoption; and as dating decisions can be construed as more "high stakes" in comparison to those in previous studies (e.g., movies or music), it might be an interesting domain in which to conduct future testing of system features like variable user control or system transparency.

Notably, the choice set manipulation indicated that daters were willing to deal with the difficulty of selecting from 200 profiles. Although choice set size significantly influenced daters' perceptions of selection task difficulty (e.g., overload), even the largest condition only produced a sense of overload equivalent to a mean of 3.22 on the 7-point scale. This suggests that daters are willing to process much larger dating pools (e.g., 804) than research indicated approximately a decade ago. For example, [40] included 90 daters in their "large" condition compared to our 804. A question for future work is to understand why increased tolerance has been observed.

One possibility is that people have adapted to higher information density in their online experiences, including online dating. The Flynn Effect, for example, describes the increase in intelligence test scores, with each generation scoring higher than previous generations, which mandates that scores be re-standardized every few years [11]. It is possible the current generation of online daters have cognitively adapted to larger dating pools than previous generations were accustomed to.

Clearly, additional work is required to examine this change in willingness to select from large sets of dating profiles, but our results suggest that need for cognition is an important factor: Daters high in NFC are willing to sift through larger profile sets making them less likely to want to use the delegated agent for smaller choice sets; it is not until they are facing 800 profiles that they recognize that the task has become too difficult and adapt their behavior. In contrast, daters lower in NFC were more likely to use the recommender when faced with any profile set size.

Although trust did not interact with choice conditions, the more trust in recommender agents people reported, the more willing they were to use the system. This is consistent with other work examining user trust [21, 22] and suggests that people's initial feelings about recommenders can affect potential use.

6.1 Limitations and Future Research

Our decision to instantiate the delegated agent condition as selecting a single dater was a deliberate effort to reflect the functionality of websites like eHarmony and apps like Only. While this enhanced ecological validity and increased experimental variance across the two recommender system conditions, future research could examine people's response to different kinds of systems that provide more variation in recommendations (e.g., a Top-N versus sort/filter interface).

We also note that the profile attributes used in the current study were modeled on the profiles of popular websites (Match.com) and apps (Tinder) that feature these specific attributes. Although the attribute manipulation did not contribute to perceptions of choice task difficulty, the limited range of these specific attributes is a limitation, and future work could examine other combinations or types of attributes to see if they affect decision-making in this context.

As our focus was on people's responses to recommenders prior to actual use, we did not examine daters' experiences with either decision aids or delegated agents. In essence, this study focused more on users' *process* as opposed to *outcomes*—"being satisfied with the system itself and the outcomes of using it are two separate concerns that may at times even be in conflict with one another" [21, p. 147]. Future work should compare daters' expectations for online dating recommender technology to their actual user experience and examine how consistent they are.

That we examined trust regarding a fictional dating service of ClassMate.com is also a limitation; however it would also be interesting to see how users' *a priori* impressions about an already existing company affect their desires to use new services. For example, general trust in Facebook has likely declined given recent events surrounding the 2016 US Presidential election (e.g., data mining by Cambridge Analytica). Would users' feelings toward Facebook as a company affect their likelihood of using the new Dating feature? Our results suggest that *a priori* trust affects users' adoption of a new system, but investigations of how trust in a familiar company may affect people's willingness to use new services offered by that company would be an exciting direction for future work.

Finally, we note the limitations associated with a college student sample—though the participants in our study are representative of the largest group of mobile and online dating users (those aged 18-24), future studies could examine recommender use among more diverse groups of daters who may approach dating (and recommender technology) differently.

6. CONCLUSION

The results of our experiment renew earlier calls to refine the design of recommender tools and move beyond the "one-size-fits all" approach [1, 17, 21, 22] and instead consider how users' personal characteristics affect their responses to technology. This appears to also be important in the online dating context, in which choice overload is a key complaint. Our results suggest that daters differ in their desire for recommenders; developers may consider offering customizable features that reflect individual differences in user personality and cognitive decision style will allow people to trust the recommender and facilitate alignment of the system with users' relational goals. Focusing on the users' psychological makeup might facilitate more effective, intelligible design of recommender systems embedded in social domains, such as online dating.

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