Spontaneous Inference of Personality Traits and Effects on Memory for Online Profiles

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Abstract

As users navigate online social spaces, they encounter numerous personal profiles, each displaying a unique constellation of attributes. How do users make sense of this information? In our first study, we provide evidence that users spontaneously make personality trait inferences about people from profiles they encounter online, and for certain profiles, preferentially remember this inferred trait content over actual profile content. Study 2 uses several measures of profile coherence to assess how the coherence of user profiles interacts with trait inferences to influence memory for profiles. Findings provide a better understanding of specific profile content that makes profiles memorable and the social-cognitive process utilized when extracting information from profiles.

Introduction

We live in the "Information Age" and the sheer amount of data that bombards us daily can be overwhelming. How can humans, as information processors, quickly and efficiently incorporate the important information and weed out the less essential? Fortunately, humans are particularly capable of this process when it comes to understanding and processing information about other human beings. In fact, this is one area where humans can still "out-process" machines. For instance, humans are experts at face recognition (Zhao, Chellappa, Phillips & Rosenfeld, 2003) This is clearly an adaptive characteristic for our species. In order for us to function in society we need to be able to recognize whether another member of our society is angry with us or is welcoming us as a friend. In the domain of personality, interpreting information about other people's personality helps us predict their behaviors in the future. For example, knowing who is selfish rather than generous helps us decide who to ask for a favor should we need one.

In recent years, individuals have begun to represent themselves online and create social networks that include self-representations in the form of online profiles. Social networks and online profiles have become critical components of computer supported social interactions, serving both social (e.g., dating site profiles) and functional purposes (e.g., networking for work). Online profiles are a unique means of self expression for users. Users may spend a great deal of time creating profiles to convey their personality to others, but how is that personality information interpreted by perceivers? Can perceivers who are bombarded with many sources of information both from within the network itself and from other competing sources adequately interpret trait information portrayed in profiles? Additionally, are profiles that effectively portray personality traits interpreted or remembered differently than those that do not?

Traditionally, research surrounding human computer interaction has provided important insight into cognitive processes behind computing (Card, Moran & Newell, 1983). Design can be informed by the users' cognitive model. As our interactions in these domains become increasingly social, additional research is needed to understand users' *social* cognitive model in order to begin to answer these questions. If researchers understand how users construe social information, software can be better designed to facilitate social interactions.

Background

Spontaneous Inferences

People need very little information to form impressions of others' traits. Work by Uleman, Newman & Moskwitz (1996) demonstrates that perceivers make "spontaneous inferences" about traits when given a small amount of behavioral information (Uleman, 1999). In the Uleman work, study participants are told to study a number of sentences describing behaviors. Some of the sentences contain strong trait content. For instance, some subjects receive "John wondered where stars come from." which cues the trait "curious". Later participants are asked to remember the individuals based on either trait cues or cues from the sentence. The key finding is that trait cues ("curious") cue memory as well or better than actual content from the sentence ("stars"). The rationale is that people are very good at extracting what information is important and personality traits often are of high utility. It may be prove more adaptive for us in the future to remember that John is a curious person so we can ask him a question than for us to remember something irrelevant about stars. In the case of online profiles, this suggests that when people are presented with profiles, they will remember personality traits as well or better than the strict content of the profiles.

It is important to keep in mind that not only do these studies find that individuals infer personality traits, but they find that they do so spontaneously. Perceivers need to merely read about a behavior, and this is sufficient to trigger a trait inference. According to Uleman (1999) these inferences are spontaneous because:

1. They are often below conscious awareness.
2. They are not intentional (not implied by the direction set).
3. They are not controllable.

In other words, perceivers infer traits in spite of their processing goals. This does not mean that controlled (within conscious awareness and intentional) trait inferences do not exist, or that automatic (below conscious awareness and unintentional) processes cannot work in parallel with controlled processes. However, Uleman's research suggests that both controlled and automatic processes are at work in the impression formation process and in fact, these processes are activated for different reasons. It is intuitive to imagine both instances when users examine profiles using controlled and spontaneous processes. For example, a casual browser on a blogging site might make inferences about profiles through spontaneous processes while an online dater looking for a romantic partner may use controlled processing. The individual looking for a romantic partner may know very well what traits they just inferred, but the casual browser may not know that they made inferences at all. We suggest that the casual browser makes more inferences than they think. Spontaneous inferences are of particular interest to us because they may guide users' choices and behavior even when those users can not elaborate them.

The "How" of Online Profile Processing

Users in computer medicated contexts must make many of the same decisions as users in face-to-face contexts. They often encounter many other user profiles and must form impressions and simultaneously remember information about these individuals. Does the impression formation process operate in the same way as in a face-to-face encounter? Computer Medicated Communication (CMC) often has fewer cues than face-to-face encounters and researchers propose two opposing theories that explain how users will integrate content from these contexts. One theory suggests that individuals will not encode as much information about other users, and will disclose less (Sproull & Kiesler, 1985). Walther (1996) and other theorists however, suggest that users pick up on minimal cues and encode whatever information is available. Communication in CMC is, according to Walter, "hyperpersonal" because the limited availability of cues causes perceivers to pick up on whatever cues are available. Users in CMC detect cues that may be overlooked in face-to-face settings to make inferences about conversation partners. For instance those in CMC use personal pronouns as contextual cues as well as pauses and lulls in conversations.

These theories allow us to begin to understand how people view those they meet and interact with online. Although this research focuses primarily on the linguistic cues that users parse, it is possible to imagine other social cues that are utilized. For example, in the current research we seek to explain the personality trait judgments people make when they encounter others online and how quickly this occurs. Thus our first study helps address the "how" of this fundamental social-cognitive process taking place online. It also enables us to make suggestions to designers and users based on social cognitive models.

The "What" of Online Profile Processing

Research shows that personal websites are fairly high fidelity representations of personality (Vazire & Gosling, 2004). One goal for this work is to start breaking down online personal representations into attributes that can then be tied to the conveyance of personality. In that vein, research has identified several attributes of online profiles that are important to users in online contexts. For instance, in an online dating context, Fiore (2002) analyzed 250,000 messages over an 8 month period and identified key profile attributes that are important to men and women. Men are interested in physical attractiveness and associated factors, whereas women are interested in education level and attractiveness. In online gaming interactions, users were best matched to other users based on distinct player types distinguished by their preferences for friendly versus aggressive play (Schiano, Nardi, Gumbrecht, & Swartz, 2004). Again displaying a distinct preference for particular profile attributes over others, in a chat room environment, users prefer to match to similar others rather than others who have good reputations (Jensen, Davis, & Farnham, 2002). Markus, Machelik & Schütz (2006) suggest that users can form impressions of others from their websites and they identify the elements of sites that help craft these impressions.

Like these previous efforts, we wanted to make predictions about how the structure of online profile content affects processing. With Study 2 we address the "what" of profile processing by examining the impact of the coherence of profile content on memory for those profiles. Study 2 continues to place an emphasis on social cognitive factors by:

Using memory as the dependent measure rather than general "preference", because it is less subjective and explicit attitudes towards profiles may not be completely representative (Greenwald & Banaji, 1995).

1. Avoiding domain specificity.
2. Considering interactions between profile structure and the trait inference process.

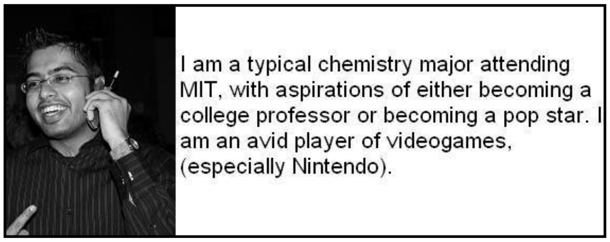

Figure 1. Sample Trait Profile. Implies "geeky".

Experimental Studies

Stimuli: Creating Profiles

For our study stimuli we created personal profiles using the following four step process.

Step 1: Personal Descriptions. Real personal descriptions were gathered from a popular blog site. Bloggers used these descriptions as an introduction to their blog in response to the item "About Me". Descriptions ranged from favorite movie quotes to descriptions of more broad personality traits.

These profiles were then altered slightly to obfuscate the identity of the individuals selected. Because the profiles contained considerable variability in length, we also standardized the length of the profiles so that each profile contained between 30-60 words. Initially we selected 55 personal descriptions for inclusion in our pilot study.

Step 2: Add Photos. Photos were obtained using an informed consent process. A separate group of participants released their photos for inclusion in the study. Photos were then matched with an appropriate personal description. We combined the personal description with the photo into a brief "about me" profile overview (See Figure 1). These were our stimulus materials throughout the studies.

Step 3: Pilot Study. In order to determine whether and what personality traits were implied by our stimuli profiles, we distributed the pilot profiles to 20 participants who were asked to write down the three characteristics they believed best defined the person in each profile. In order for the profile to be included in our study, 50% or more of the participants had to describe the profile using the same trait or a close synonym. The trait terms used were the colloquial terms rather than researcher driven names (i.e. "geeky" not "intelligent"). The purpose of this piloting was to ensure that the stimuli profiles included in the final study did in fact contain traits that perceivers could extract. This technique of trait listing is borrowed from previous research on spontaneous trait inferences (Uleman et al., 1996; Uleman, 1999). 32 profiles were included in the final studies.

Step 4: Semantic Profiles. After creating trait implying profiles in steps 1-3, we created "semantic" versions for each stimulus profile by removing the trait implication. For instance instead of reading "I am a typical chemistry major attending MIT, with aspirations of either becoming a college professor or becoming a pop star. I am an avid player of videogames (especially Nintendo).", the semantic version of the above profile reads, "I am a typical college student with aspirations of either becoming a teacher or becoming a pop star. I am an avid player of video games (especially Nintendo)." In this version, the trait implication of "geeky" is removed (or significantly weakened) by diluting the implications of his academic affiliations (MIT), his scientific major and his career aspirations. In all the semantic profiles, we preserved as much of the content from the original trait implying profile as possible. The inclusion of semantic profiles in our study allows us to rule out the suggestion that our effects are due to the profile pictures alone. Each picture was assigned to a trait profile and a matched semantic profile, allowing us to compare memory for trait and semantic profiles.

Note that for our research purposes we created a somewhat simplified profile, containing a photo and personal statement. We felt that these abbreviated profiles made our research tractable while maintaining sufficient realism in that users often make choices based on these types of profiles, such as whether this is a person who's blog they would like to read.

Study 1

Hypotheses.

1. Individuals make personality trait inferences when viewing online profiles.
2. These inferences can be "spontaneous".

Demographics. Our first study included 31 participants who were recruited via email. None of the participants were known by the experimenters. Twenty-three male participants and eight female participants took part in our study. Twenty-two participants were Caucasian, 5 were Asian, 3 were African-American and one was "other". Participants ranged in age from 19 to 49 years with an average age of 33.5.

Participants reported having experience with social networking sites. On average participants had 2.5 years of experience and spent an average of 2.19 hours a week on these sites. In addition, participants posted an average of 3.73 profiles in their lifetime.

Method. Participants were told that they would view a number of online profiles that were "About Me" sections from a popular blogging site and also warned that some details had been changed to protect the identities of the individuals portrayed. After consenting to participate, participants were given very general instructions to "form an impression" about the profiles they were to view. This kept the experience as realistic as possible for participants while not instructing them to remember any specific information, thus allowing for spontaneous processing.

Using methods from social psychology, we adapted our profiles to a cued-recall technique that is widely accepted for detecting spontaneous inferences (Uleman, 1999). This procedure utilizes Tulving's encoding specificity principle (Tulving, 1972; Uleman et al., 1996). If secondary information is present while primary information is being encoded, secondary information will serve as a cue for the

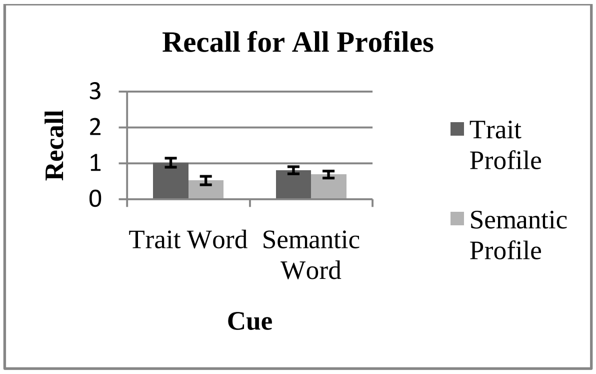

Figure 2: Recall based on condition. Memory ranges from 0 = no recall of profile content to 3 = complete recall of profile content. Error Bars= S.E.

primary information. Therefore, if people make a personality trait inference when they read a profile, then traits should serve as memory cues to help remember those profiles (Uleman et al., 1996). If this trait inference is especially strong, then traits will be as good of a cue or better as content from the profile. Trait cues will not help if this personality trait was not present in the profile. This procedure was administered using two study–recall phases.

Study Phase 1. During the first study phase participants were asked to view 16 profiles. Profiles were presented on screen for 10 seconds each. Participants had to press "continue" after each profile to move on with the experiment. This was to ensure each profile was viewed. The order of the 16 profiles was randomized. Eight trait profiles and eight semantic profiles were presented.

Recall Phase 1. In the recall phase participants are presented with either trait cues or semantic cues in the form of words shown on screen and asked to use these as prompts to recall the profile information they read about earlier. Semantic cues were words (e.g., "Nintendo") that were actually contained in the profile while trait cues were trait words (e.g., "geeky") that were not contained explicitly in the profile but were cued in trait profiles. The trait cue words were those provided by our pilot study participants who initially evaluated the profiles for the presence of a trait, which ensured that the trait cue words were well-matched to the trait profile stimuli. Subjects were given a blank space below the cue to provide as much of the personal description as they could remember based on the cue. After one practice trial, participants completed this cued recall procedure for each of the 16 profiles shown in the study phase of the experiment.

We randomized the stimuli but ensured there were the same numbers of each type per cell to control for order effects (Table 1). Each subject received eight of each profile/cue combination.

Study Phase 2- Recall Phase 2. The procedure described above was repeated with 16 more profiles so that participants saw a total of 32 profiles in two sets of study-recall phases. The study was broken into two parts because pilot testing demonstrated that participants did not have the capacity to remember sufficient information from 32 profiles.

Measures. As noted, this was a cued-recall task. Our dependent measure was recall for the profile content when cued. Raters who were blind to the participants' condition coded the recall on a scale of 0-3 (no recall- complete recall). No recall meant that when cued, the participant was unable to type in any amount of the profile "About Me" statement. Complete recall meant that the participant reproduced the entire "About Me" statement when cued. Most frequently, participants recalled some part of the "About Me" statement.

Note that some words cued a profile that was not the "intended" profile. For instance, when presented with the trait word "geeky", individuals may have recalled a different profile than the profile the experimenters had in mind. Because many profiles did imply similar traits, we felt it necessary to account for this and included these scores in our analysis. Less than 5% of the words recalled fell into this category. Additionally, semantic and even trait profiles may have cued other traits (e.g., the "geeky" profile in Figure 1 may have cued the trait "achiever"). However because these traits were not provided as cues, we assume this did not affect recall scores.

Study 1

We were interested in what type of information helped cue recall for participants. Results from our 2 x 2 ANOVA show that there was no main effect of word, $F(1, 30)=0.01$, $p<0.987$. There was however, a significant main effect of profile such that trait profiles were preferentially recalled, $F(1, 31)=21.4$, $p<0.001$. The trait word- trait profile pairing was of particular interest to us. Simple effects of profile for demonstrated a simple effect of profile for trait words, $F(1, 31)=51.8$, $p<0.001$. There was no simple effect of profile when the cue was a semantic word, $F(1, 31)=1.01$, $p=0.322$. Trait profiles were remembered better when the cue was a trait word ($M=1.02$) but not when the cue was a semantic word ($M=0.52$). Finally, there was an overall profile x word interaction, $F(1, 31)=35.3$, $p<0.001$. This interaction is presented in Figure 2.

These findings demonstrate that traits serve as better recall cues than semantic words but only when profiles imply relevant traits. Therefore, it seems that participants remember the overall trait content of the profile better than the actual semantic content of the profiles they are presented with. They cannot however, extract trait content if that trait is not implied.

Anecdotal Evidence for Spontaneous Trait Inferences. It is also interesting to note that participants responding to semantic cue words often spontaneously generated trait information during recall. For instance, one subject recalls "the seemingly self-centered girl who also liked Louis Vuitton and diamonds", when prompted with the cue "perfumes". Although the participant was simply asked to recall the profile, the participant felt it diagnostic to note trait information ("self-centered") in addition to actual profile content. Another recalls, "sports jock that will take mother out to a seafood dinner" simply because the target was wearing a track uniform although the target indicated nothing about sports in his profile. Although we did not systematically analyze this content, it seems that dispositional processing of information is implicit and, as we hypothesize, spontaneous.

Discussion, Study 1

We designed our first study to examine whether:
Individuals better remember people in online profiles using trait inferences than from the actual content of the profiles. These trait inferences can be "spontaneous".

We demonstrated that, like people who meet others in real world interactions, users in online communities are skilled at extracting important trait information from messy data. In fact, when users view profiles they may remember information about personality traits of other users more than the actual content of the profiles they view. However, this is only true if these profiles imply this trait.

Not only do perceivers extract traits from online profiles, but they also do so spontaneously. Without any explicit instructions or processing goals, they still made inferences about users' personality traits. By simply reading a series of brief profiles containing varying content, perceivers remembered personality traits they inferred about other users. Trait information was remembered preferentially to profile content.

Although absolute differences between conditions may be small they were both statistically significant and meaningful. Our overall numbers are low because of the difficulty of using free recall rather than recognition to identify other users. The recall task was challenging. Also, trait profiles are remembered 30% more than semantic profiles, and trait words trigger recall 20% more than semantic words that were actually contained in the profile.

This finding led us to hypothesize that there may be factors about the target profile that affect memory. We therefore devised a second study to examine these factors.

Study 2

Study 1 demonstrated that users make spontaneous trait inferences when profiles clearly imply traits. Therefore, we see a difference between profiles crafted to imply a clear personality and those not designed to do so. Are there other factors affecting memory for traits? We used Study 1 as a building block to identify factors of profiles that might be related to recall. Since trait profiles in Study 1 cohered on a common trait, perhaps coherence in general is related to recall for profiles. Coherent profiles may allow participants to form more structured impressions, and lead to better memory. Again, we are interested in identifying models that are easiest to process for users. Coherency may be one dimension that makes social information easier to process.

Hypothesis. There is a positive relationship between profile coherence and overall recall.

Method

We assessed coherence using three measures:

1. Overall Coherence: How well do profile elements fit together?
2. Number of Elements: How many particular elements does the profile contain?
3. Specificity: How specific is each particular element?

Overall Coherence. Pilot study participants were asked to rate the coherence of the 64 stimuli profiles (32 trait and 32 semantic). Profiles were broken into 3 segments. Three participants were told to compare each part of the profile to the other 2 parts and rate how well the parts "went together" using a 1-7 Likert scale. Interrater reliability was good (α=0.97). Higher coherence scores are hypothesized to be associated with higher recall.

Number of Elements. We asked a second group of pilot participants to divide each profile into its constituent elements. Nine participants were presented with all 64 profiles (trait and semantic). Participants were asked to divide each profile into elements that were psychologically meaningful for them by simply recording and labeling these separate parts. Participants' breakdowns ranged from 1-10 elements. Interrater reliability was good (α=0.81). For example, the profile in Figure 1: "I am a typical chemistry major attending MIT, with aspirations of either becoming a college professor or becoming a pop star. I am an avid player of videogames, (especially Nintendo)." might be broken down as, "1) I am a typical chemistry major attending MIT 2) with aspirations of either becoming a college professor 3)or a pop star. 4) I am an avid player of videogames, (especially Nintendo)." Because this participant felt that these 4 items roughly cohered psychologically, they broke the profile into 4 elements. We expect that profiles with fewer items are associated with greater coherence and will be remembered better.

Specificity: A third group of three pilot study participants were assigned to rate the specificity of the profiles. Profiles were again broken into 3 parts. Participants rated the specificity of each part of the profile from 1-7 on a Likert scale. The final specificity score for each profile was a sum of the three ratings. Again interrater reliability was good (α=0.93). We expect that profiles with higher specificity scores will be remembered better.

For purposes of illustration in Table 2 we included text from the profiles with the highest and lowest scores in each information category.

Results

For each coherence measure we calculated the correlation between coherence (e.g., low to high specificity of profile elements) of the profiles with the recall scores for those profiles we collected in study 1. Correlations for trait and semantic profiles are also examined separately for each measure of coherence.

Table 2. Sample Profile Text: Highest and lowest rated profiles for each category

Sample Profile Text	**Highest**	**Lowest**
Overall Coherence	Ummmmm, yeah. I occasionally attend class at UCSD, im a junior here. I really like sleeping and watching tv. I'm a huge procrastinator. Umm, well here's my life.	i have id say about 5 friends but then again I think I don't need a lot. i think if u have a cuple TRUE friends then ur fine!! I also have glasses and braces! I act different to other ppl sumtimes.
Number of Items	helloo, =] I adore ADRIEN BRODY, ORLANDO BLOOM, perfumes, diamonds, roses, couture, jazz, louis vuitton, chanel, Gucci, gold & loads more. I think my xanga site is hot & appreciate it if you read, u blog & post some comments <3	The thing you need to know is that 88% of sites suck… that may be yours also thankfully, I balance the world, so yay me you inebriated simian miscreants.
Specificity	I will smash your face into a car windshield and then take your mother, Dorothy, out to a nice seafood dinner and NEVER call her again!	Im your typical girl, that goes thorough the normal ups and downs in life... but i like to add a romantic twist some times....I like to try new things...that sometimes get me into trouble...but it makes my life so much more fun and interesting!

Overall Coherence. We found the predicted positive correlation between overall recall and overall coherence (r=0.19). However, since this correlation was not as strong as expected, we looked at correlations for trait and semantic profiles separately and saw this positive relationship was stronger for trait profiles (r=0.22) and more modest (although not negative) for semantic profiles (r=0.12).

Number of Elements. When we examined the correlation between the number of elements in the profile and overall recall for that profile, the predicted negative correlation did not emerge (r=0.042). However, once the data were separated into trait and semantic profiles, we see that the presence of a trait mediates this effect. For profiles that implied traits, as was hypothesized, the number of items in the profile was negatively related to memory for the profile (r=-0.28). However for profiles that did not imply traits, the number of items in the profile was positively correlated to memory for the profile (r=0.33). See Figure 3 for scatterplots of the relationship between the number of elements and recall for both trait and semantic profiles.

Specificity. There was no positive relationship between specificity and recall for profiles (r=-0.09). Within the separate profile conditions, effects are also nonsignificant (r=-0.159) for trait profiles, and (r=-0.04) for semantic profiles.

Intercorrelation. As expected these items are related but not the same. Specificity and the number of items are significantly correlated, r=-0.41, p<0.001. More specific profiles have fewer items. However, the overall coherency was not related to the number of items, r=0.14, p=0.14 and the overall coherency and the specificity were not related, r=-0.01, p=0.47.

Individual Differences. Although we did not see the predicted effects of either trait or semantic profiles when looking at the relationship between specificity and recall, we hypothesized that there are factors other than the presence of a trait that mediate this relationship. People differ in their responses and interests. Previously we averaged across all participants, which may have caused us to ignore effects at the level of the individual. We looked at correlations between the average recall scores for each profile established in Study 1 and each individual participant's responses to our three coherence measures. This enabled us to determine if there were cognitive mediators at the level of the person rather than the level of the profile that drive the relationship between specificity and recall. If some participants exhibited strongly positive and others strongly negative correlations between recall and specificity, we hypothesize that these mediators exist and deserve more attention.

Correlations ranged from r=-0.49 to r=0.69 for trait profiles and r=-0.33 to r=0.58 for semantic profiles. For illustrative purposes, Figure 4 displays sample participants' correlations between recall and specificity for both trait and semantic profiles. Individuals exhibit high correlations between specificity and recall in both the negative and positive direction.

Since individuals exhibited both significant positive and negative correlations between specificity and recall within trait and semantic conditions, we hypothesized that there were also important effects for the overall coherence measure and number of elements measure. The overall coherence measure yielded diverse and strong correlations in both the positive and negative direction ranging from r=-0.58 to r=0.55 for trait profiles and r=-0.56 and r=0.64 for semantic profiles. Additionally, when we looked at the relationship between recall for each individual participant and the number of elements in each profile, participants displayed strong correlations in both the negative and positive direction, from r=-0.45 to r=0.47 and r=-0.65 to r=0.59 for trait and semantic profiles respectively. A graph representing the highest and lowest correlations for all

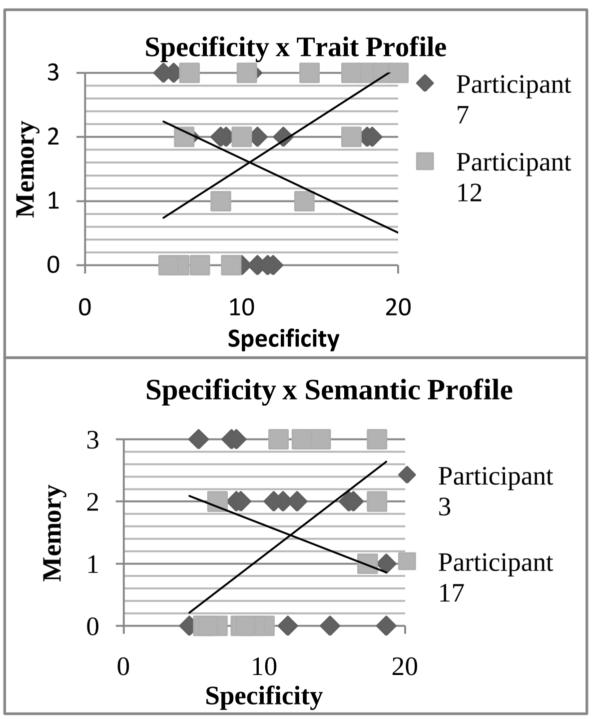

Figure 4: Individual Response Patterns for Specificity within Each Profile Condition

measures of coherence is displayed in Figure 5. The average overall correlation for semantic and trait profiles on that dimension is also provided for reference.

Discussion: Study 2

Study 2, like Study 1 emphasizes the importance of unifying information within a profile. In Study 1, when traits were present, they served as powerful cues for the observer. In Study 2, certain measures of coherency

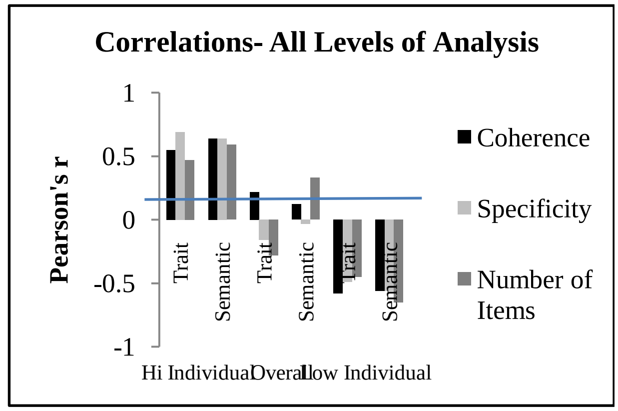

Figure 5. Correlations for each level of analysis and attribute.

provided evidence that perceivers remembered coherent profiles better. Profiles that are internally consistent (all the elements relate to each other) are most apt to be recalled. Participants also remember profiles that had fewer elements (another proposed measure of coherence), although this was

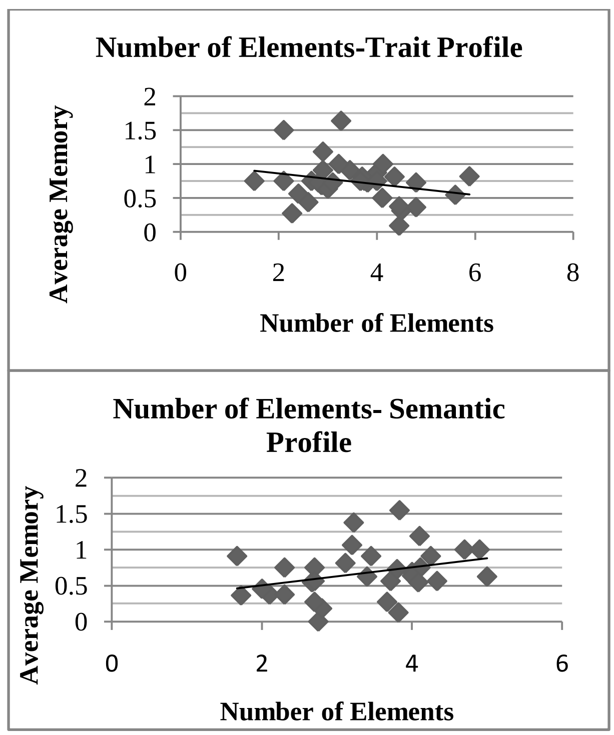

Figure 3: Number of Elements x Recall for Trait and Semantic Profiles

only true when a trait was present suggesting that traits may serve as a mediating variable in some situations. We also discovered that each user is unique and will not react to the profile attributes with the same pattern of response. For instance, highly specific profiles may be very memorable to some but not contain the features that another user is looking for at all.

Specific results for each coherency measure are discussed below:

Overall Coherence. Our overall coherence measure asked participants to relate intra-profile coherence. To the extent that the items within the profile matched well together, the profile was remembered better. This was particularly true when a trait was present.

Number of Attributes. When participants broke profiles into their constituent elements, the presence of a trait served as a mediator for the relationship between recall and this measure of coherence. To improve recall, profiles that contain traits should be condensed into a few trait implying elements. Conversely, for those that do not imply a trait, more elements seem to lead to a more memorable profile.

Specificity. Our findings for the specificity dimension were not as hypothesized: there was no overall relationship between profile specificity and memory. However, once we broke the profiles down and examined individual patterns of response, we determined that there were in fact, correlations between specificity and memory, but because they ranged in both directions, averaging across all participants did not account for individual responses to specific profiles. Additional research is needed to determine the individual difference factors that drive the relationship between specificity and recall.

Conclusion

As people become increasingly social in online domains, we are able to study the social cognitive aspects of their complex interactions. From these studies, we propose that personality traits can be inferred spontaneously from online profiles and that they are extracted preferentially to other content (Study 1). We also identified information in addition to trait content that allows users to process profiles more effectively (Study 2). As a general trend, coherency facilitates memory for profiles, implying that it allows for more efficient processing of social information. This is especially true when trait information is present in user profiles. Finally, we argue that each user is unique and it is important to attend to their unique patterns of responding.

Knowing *how* users make inferences in social networks and computer mediated contexts has important theoretical and practical applications. Users made trait inferences from online profiles. Additionally, they formed these impressions on the basis of little information and without prior instruction sets. These studies suggest that users engage in hyperpersonal communiation online and user behavior in online domains replicates user behavior in offline domains (Uleman, 1999; Uleman et al., 1996). Impression formation online is a natural and automatic process. Users will draw inferences about personalities of the other people they encounter.

These studies also suggest that users process coherent profile information more readily. Specifically, if profile elements fit together, this aids in profile memory. If profiles cue a trait then it is especially important for them to be coherent. Simultaneously, it is important to keep in mind that, despite general trends, people process social information in different ways (e.g., memory for profiles is facilitated by highly specific profile content for some users but not for others). Our individual difference findings from Study 2 highlight the importance of customization for the individual user. We hope to use this study as a launch pad to better categorize individual patterns of responding into clear focus groups. For instance, there may be individuals who prefer a certain attribute such as specificity and not another. How can we a priori tag these individuals as part of this preference group?

There are a number of services, typically aimed at dating sites, that offer tips for the look and feel of the profile, but it is reasonable to imagine many types of users wish to be remembered. For instance, there are bloggers who want people to return to their site to hear their views again. With these studies, we show that memory for a profile has to do with more than just look and feel, and again we point to the importance of the promise to boost recall for their profiles by 30% by their inclusion of a trait.

How then can these findings help designers facilitate interpersonal interactions online and what suggestions can we provide to users creating online profiles based on this research? Personality trait inferences are natural in online domains but they are facilitated only if a trait is implied in the online profile. Therefore we suggest that for any context where users want to be remembered, users and designers create profiles and profile environments where trait implications are natural and encouraged. For instance, the blogging site that first displays the "About Me" section is organized for better memory than the site that first displays demographic information that has less probability of cueing a trait. In addition to organizational enhancements, services could promote memory for profiles by providing instruction sets that help users convey a trait, even if this is as simple as telling users to do so explicitly.

As a somewhat more sophisticated alternative, a site could solicit trait tags for profiles from other users as a way to check whether profiles are in fact conveying a trait, and if so, what trait they are conveying. Users could rate one another on personality dimensions and adjust their profile content based on their ratings. Finally, it may also be possible parse the language used in profiles to identify the strength of the traits conveyed using natural language processing programs Natural language processing programs have already been used in ecommerce to acquire implicit and explicit user data such as mood, values (implicit) and product references (explicit) from user postings and emails (Paik, Sibel, Brown, Poulin, Dubon, & Amice, 2001). These programs could be applied to mine both implicit and explicit references to traits in user profiles.

In sum, we believe that people are social processors of information and it is this social information that drives their behavior. People demonstrate preferences for trait information because they are trying to make sense of complicated the social networks that surround them. Their ability to quickly and efficiently extract traits is a skill that is most essentially human and, as this study demonstrates, carries over fluently to online interactions.

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