# Spontaneous inferences on social media and their implications for ambient awareness

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# Summary

*Ambient awareness* refers to the idea that social media users gain awareness of their online networks, while sifting through the stream of social updates spontaneously, without deliberate effort or intention. Since online networks are large and diverse, an efficient process like ambient awareness has important implications for how people can manage to maintain and profit from them (Donath, 2007; Resnick, 2001). Despite its growing popularity in social media research, ambient awareness had not been studied systematically and there had been no unequivocal evidence that it can develop peripherally, that is, from fragmented information and in the relative absence of prior acquaintanceship and extensive communication. The objective of this dissertation was to examine the spontaneous inference processes implicated in ambient awareness. Two exploratory surveys revealed that users of a microblogging site experience ambient awareness and are able to report specific knowledge of people whose updates they follow but whom they had not met in real life. These results strongly suggested that microblogging posts are sufficient for ambient awareness to develop. To test whether ambient awareness can indeed arise spontaneously, I adapted a paradigm from psychological research on spontaneous trait inferences. A series of experiments revealed that after viewing social media posts, people spontaneously formed accurate impressions of the actors who had ostensibly written the posts. These impressions included traits as well as domains of expertise, such as programmer or photographer. Another insight was that the amount of exposure and content had downstream consequences of people's impressions of competence and approachability. That people infer crucial information spontaneously while browsing social media is a premise underlying most reasoning surrounding ambient awareness. These studies are the first to directly test it. Via social media, people receive a steady stream of updates and notifications from their extended networks, but this information is fragmented and too much to carefully processes and remember. The results of my dissertation suggest that even in such conditions, people are able extract information, which allows to make sense of who is who and who knows what in their vast online networks.

# Zusammenfassung

Der Begriff *ambient awareness* umfasst die Idee, dass Nutzer sozialer Medien Kenntnis über ihre Online-Netzwerke erlangen während sie, ohne vorsätzliche Anstrengung oder Absicht, den Strom sozialer Updates durchkämmen. Da online Netzwerke groß und divers sind, kann ein effizienter Prozess wie Ambient Awareness wichtige Auswirkungen darauf haben, wie Menschen ihre Netzwerke organisieren und von ihnen profitieren können (Donath, 2007; Resnick, 2001).

Trotz der wachsenden Popularität des Forschungsfeldes "Soziale Medien", wurde Ambient Awareness bislang noch nicht systematisch erforscht, so gab es keine eindeutige Definition und auch keine Hinweise darauf, dass Ambient Awareness peripheral, das heißt auf Grundlage fragmentierter Informationen und in weitgehender Abwesenheit von vorher-bestehender Bekanntschaft und umfassender Kommunikation zwischen Personen, entstehen kann. Das Ziel dieser Dissertation ist es, spontane Inferenzprozesse, welche Ambient Awareness implizieren, zu untersuchen.

Zwei explorative Studien zeigten, dass Nutzer von Microblogging-Seiten Ambient Awareness erleben und, dass sie in der Lage sind spezifisches Wissen bezüglich derjenigen Menschen dessen Updates sie folgen wiederzugeben – ohne diese Personen zuvor im echten Leben getroffen zu haben. Diese Ergebnisse legen Nahe, dass Microblogging-Beiträge ausreichend sind, damit Ambient Awareness entsteht. Um zu testen, ob sich Ambient Awareness in der Tat spontan entwickeln kann, habe ich das Paradigma der sogenannten 'spontaneous trait inferences' aus der psychologischen Forschung an Ambient Awareness angepasst. Eine Serie von Experimenten zeigte, dass Personen nach dem Lesen von Beiträgen aus sozialen Medien spontan akkurate Eindrücke von den vorgeblichen Verfassern geformt hatten. Diese Eindrücke enthielten Charaktereigenschaften, aber auch Expertenwissen, zum Beispiel Kenntnis ber den Beruf: Programmierer (Programmieren) oder Fotograf (Fotografie). Eine weitere Erkenntnis war, dass die Häufigkeit und der Inhalt von Beiträgen Konsequenzen auf die gewonnenen Eindrücke hinsichtlich Kompetenz und Zugänglichkeit hatten. Dass Menschen spontan wichtige Informationen ableiten während sie durch soziale Netzwerke browsen, ist eine Prämisse, die in der Ambient Awareness Diskussion oft vorausgesetzt wird – diese Studien sind die ersten, die diese Annahme direkt testen.

Durch soziale Medien erhalten Menschen einen stetigen Fluss von Updates und Benachrichtigungen aus ihrem erweiterten sozialen Netzwerk. Diese Informationen sind jedoch zu fragmentiert und zu zahlreich um aufmerksam und bewusst wahrgenommen und langfristig behalten zu werden. Wie die Ergebnisse meiner Dissertation zeigen, sind Menschen dennoch in der Lage, sich aus der Vielzahl von Informationen und Informationsbruchstcken diejenigen herauszufiltern, die Ihnen dabei helfen sich in ihren weitlufigen Online-Netzwerken zurechtzufinden und zu wissen wer was macht, und wer was weiß.

# List of publications

- Levordashka, A., & Utz, S. (2016). Ambient awareness: From random noise to digital closeness in online social networks. *Computers in Human Behavior, 60*, 147-154. doi:10.1016/j.chb.2016.02.037
- Levordashka, A., & Utz, S. (2017). Spontaneous trait inferences on social media. *Social Psychological and Personality Science, 8*, 93-101. doi:10.1177/1948550616663803
- Levordashka, A., & Utz, S. (Submitted). Ambient awareness of who knows what: Spontaneous inferences of domain expertise.

For all three projects, the research questions and overall design were developed by Ana Levordashka and Sonja Utz. The studies were designed, conducted, and analyzed by Ana Levordashka with feedback from Sonja Utz. The papers were written by Ana Levordashka with feedback from Sonja Utz. For more details, see Appendix E.

# 1. Introduction

Every person needs information. For a knowledge worker this could be help solving a task, for a job seeker it could be finding out about an interesting offer, and for just about anyone it could be getting a good vacation tip or a book recommendation. In research, these are called informational benefits and can be formally defined as "timely access to novel, valuable information" (Burt, 1992, as cited in Utz, 2015). Social connections are an invaluable source of informational support, which is why scholars refer to them social capital (Adler & Kwon, 2002). Social media make it easy to connect with people at virtually no cost and effort (Tong & Walther, 2011). Perhaps not surprisingly, there have been great expectations with regard to social media's potential social and informational benefits (Donath, 2007; Resnick, 2001).

Two ways in which social media have been proposed to enhance information exchange are by helping seekers identify sources of information and by improving the relationship between the information seekers and sources (Fulk & Yuan, 2013). Social media can be used to gain such information deliberately. For example, a researcher who plans to approach a potential collaborator might choose to look at this person's social media activity to find out if they seem approachable and to get a sense of who they are. With regard to who knows what, a symposium organizer who wants to hire a speaker with certain expertise, can query LinkedIn and review the profiles of potential candidates. In each of these cases, social media further facilitate communication by providing easy, inexpensive ways to contact people. Although relevant, these active processes are not the focus of my dissertation. Instead, I consider whether people gain such awareness while only sifting through their newsfeeds and notifications and whether this happens spontaneously, without deliberate effort or intention. This idea is referred to as *ambient awareness* and can be best defined as "awareness of social others, arising from the frequent reception of fragmented personal information, such as status updates and various digital footprints, while browsing social media." In the examples above, ambient awareness would be the equivalent of the researcher bumping into a potential collaborator and happening to know that this potential collaborator is a friendly, sociable person who enjoys skiing, which presents an easy way to strike up a conversation. The symposium organizer realizes that they happen to know of several people who fit the desired profile. Such a process carries important implications. Social media users already spend a substantial amount of time browsing their newsfeeds (Vorderer et al., 2016), whereas the deliberate, active query of available repositories is hindered by various cognitive and motivational factors (Hinds & Pfeffer, 2003). Besides, the copious amount of content available online makes it difficult to find relevant information on demand even if motivation were present.

Overall, the answer of the question of whether social media contribute to informational processes has been 'yes' (Chui et al., 2012; Leonardi et al., 2013). Recently the association between social media use and informational benefits has been demonstrated in a sample representative of the Dutch population (Utz & Breuer, 2016). But what underlies this association is unclear. By definition, having more contact increases the amount of potentially accessible information (Granovetter, 1973). However, the mere availability of information is not the same as being able to access it. Information exchange is a complex, multi-faceted process, which involves locating sources of information, approaching them, and receiving helpful answers (Austin, 2003; Fulk & Yuan, 2013; Levin & Cross, 2004). To understand the benefits of social media use, one would need to look at the challenges and problems of information exchange and how social media help resolve them.

Ambient awareness plays a central role in theories regarding the benefits of social media use (Hampton et al., 2011; Leonardi, 2015; Rice et al., 2017; Utz, 2016), but the empirical evidence for its existence is limited. Furthermore, the central premise that it develops peripherally, not through deliberately attending to information, but rather as an artifact of browsing, has not been tested. The present research examines ambient awareness and the processes that underlie it.

## 1.1 Ambient Awareness

Originally, ambient awareness has been used to describe the sense of familiarity stemming from physical co-presence. Without ever talking to the coworker across the hall, over time we end up knowing quite a bit about her simply by catching a glimpse of an 'Open Science' t-shirt, hearing a Radiohead song behind her closed door, and seeing her leave the office to make a cappuccino five times a day. The resulting awareness can come in handy if we are to strike up a conversation or need advice for the best coffee joints in the city. Informal communication serves a similar purpose (Kraut et al., 2002). To phrase this in a less anecdotal manner, people are a valuable resource of social and informational support (Adler & Kwon, 2002) and some level of awareness is important for building and maintaining relationships (Fulk & Yuan, 2013; Resnick, 2001). With computer-mediated communication and especially social media, physical co-presence is no longer required and informal communication is less common. This has naturally raised concerns of how to enable these vital aspects of social interaction. Early work has focused on enhancing ambient awareness through emulating co-presence (e.g., Liechti & Ichikawa, 2000). Essentially, the idea of ambient awareness via social media can develop despite being devoid of classic audiovisual cues, due to the incessant stream of social information. Typically brief and momentary, single pieces of information are not particularly informative and rarely devoted more than a passing glance, but over time the accumulation of fragmented personal information brings about awareness (Kaplan, 2012; Leonardi, 2015; Thompson, 2008; Utz, 2016).

The idea that awareness can develop on the basis of minimal content such as status updates, is conceptually supported by research in computer-mediated communication and psychology. According to the social information processing theory and the hyperpersonal model (Walther, 1996, 2007), people use whatever cues are available to them to form impressions. Psychological research on spontaneous inferences from brief instances of behavior has consistently demonstrated that people spontaneously extract potentially valuable information, even in conditions of superficial processing and under high cognitive or information load (Uleman et al., 2008). Research has found this to be the case for various types of information, including traits, values, and, more recently, social roles (Chen et al., 2014). Although conceptually related, most existing research on spontaneous trait inferences differs from social media in important ways that prevent direct generalization. Social-media posts are composed by the person to whom they refer. Such self-generated descriptions might be less diagnostic and reliable than other-generated cues (Utz, 2010). Furthermore, rather than seen one at a time, status updates are often received in aggregate with updates from a number of people presented together in somewhat chronological order (e.g., Facebook's Newsfeed; Twitter's Timeline), which is likely to influence how they are processed. In research on online impression formation, it is common to explicitly ask participants to judge others, whose profiles they view at their own pace, whereas browsing involves skimming through information without any particular intention. Even if the encountered posts contain relevant cues, it is not clear whether these cues will lead to inferences when people encounter them briefly and without explicit impression formation goals.

### 1.1.1 Awareness of who is who

Familiarity and liking play a crucial role in interpersonal processes and knowledge exchange is no exception (Andrews & Delahaye, 2000). People are likely to seek information from others who appear approachable and easy to reach out to (Auster & Wei Choo, 1994; Lu & Yuan, 2011). Familiarity between interaction partners can lead to establishing a common ground (Clark & Brennan, 1991) or provide a topic for starting a conversation, or inform strategic self-presentation (Hancock et al., 2008). Since asking for help or advice tends to involve disclosing sensitive information (gaps in knowledge at the very least), some degree of trust in the information source is required (Levin & Cross, 2004).

Several case and intervention studies on the use of awareness-enhancing technologies have found positive outcomes in terms of feelings of connectedness, intimacy, and well-being (Cornejo et al., 2013; Ito, 2005; Romero et al., 2007). In qualitative studies on social media use in organizations, people describe ambient awareness as a result of using microblogging sites. Awareness was perceived as having positive impact on information sharing, common ground in meetings, and contextual social presence (Zhao et al., 2011); connecting with colleagues and especially with distant colleagues (Dimicco et al., 2008); and receiving help, gaining access to breaking news, picking up trends, and feeling connected (Ehrlich & Shami, 2010). In these studies, ambient awareness has been described in detail and illustrated with compelling anecdotal examples, but these sources provide no quantitative data to support and clarify the suggested process. More recent work done within organizations showed that using social media indeed facilitates knowledge exchange (Leonardi, 2015). When complex knowledge from social others was needed, knowledge transfer was more successful and satisfying if people delayed asking and used social networking sites to gain awareness for the knowledge sources, prior to approaching them. Awareness in this study was inferred from specific networking activities (e.g., browsing profiles), which their participants reported to have performed. Surveys have found a positive effect of social media use on network diversity and access to social capital, both directly through online activities and indirectly through promoting participation in traditional, offline settings (Hampton et al., 2011). The authors attribute the effect to awareness, because it enables visibility and flow of information between different people and groups, thereby bridging the boundaries between them and likely increasing social capital. Awareness itself was not assessed.

The few quantitative studies which address ambient awareness, offer no definitive operationalization and measurement. Instead, some authors speculate its presence (Hampton et al., 2011) or equate it with social media use (Leonardi, 2015). While these practices can be suited for answering the research questions addressed in each respective paper, they fail to offer a comprehensive account of ambient awareness and leave a number of open questions related to its content and prevalence.

### 1.1.2 Awareness of who knows what

Being able to recognize the expertise of others is one of the core components of transactive memory (Lewis & Herndon, 2011; Wegner, 1987) – a prominent theory of group cognition, according to which groups develop awareness of who knows what (expertise awareness) and this allows them to coordinate tasks and information. The resulting performance benefits have been widely-documented: Research on teams and organizations has consistently demonstrated that expertise recognition and the subsequent awareness of who knows what enhance knowledge processes (Austin, 2003; Lewis, 2004, but see also: Ray et al., 2012). Similarly, in personal and professional social networks, awareness of who knows what can help people locate potential sources of information, thus helping people gain timely access to valuable information.

Awareness of who knows what is known to be higher among well-acquainted individuals (Hollingshead, 1998; Wegner et al., 1991) and to develop in the course of communication (Lewis, 2004). Less is known about its antecedents among strangers. Gaining information from close others is not optimal. Structurally, the prevalence of novel information is more likely to be higher among weak ties (Granovetter, 1973). The role of digital technologies has been examined primarily with regard to providing people with information regarding others' expertise via knowledge management systems (Alavi & Leidner, 2001). However, knowledge repositories are not used in optimal, effective ways (Hinds & Pfeffer, 2003). More recently, researchers have considered how the light-weight communication on social media and networking sites might facilitate expertise awareness (Fulk & Yuan, 2013; Leonardi & Meyer, 2015).

Transactive memory has been researched mainly in the context of organisational knowledge exchange, but might in fact play an important role in how individuals can benefit from their personal networks. Digital technologies enable its users to build large networks and connect with people who can potentially provide useful information, but without knowing whom to approach, gaining access to this information can be difficult. Making public requests, for example, could involve self-disclosure, which might be undesirable or even risky (Vitak & Ellison, 2012). Being aware of who knows what could help locate potential sources of information to approach directly, thus avoiding public requests.

Evidence for ambient awareness and its potential role in information exchange comes from a number of recent studies. Leonardi (2015) found that after using social media, employees had better awareness of who knows what in their department. The participants reported both the frequency with which they "happened to notice" versus "spent time carefully reading" information about others and it was the former that better predicted the subsequent awareness. Another study found that people were more satisfied with knowledge transfer, if they used social media to find out more about their communication partners before actually approaching them (Leonardi & Meyer, 2015).

These studies highlight the importance of ambient awareness but fail to provide a convincing test of the major premise that awareness arises without deliberate effort or intention. Surveys measure user activity and correlate it to perceived levels of awareness. However, they are not able to validate the accuracy of people's perceptions. Studies done within organizations could validate the accuracy of awareness, but could not rule out the influence of prior acquaintanceship, face-to-face interactions, and motivation, since they were conducted in a workplace context where people interact frequently and topics related to expertise are particularly salient.

## 1.2 Objectives

Despite its growing popularity in social media research, ambient awareness had not been studied systematically and there had been no clear definition or evidence that it can develop peripherally, that is, from fragmented information and in the relative absence of prior acquaintanceship and extensive communication. Based on the literature on social information processing (Walther, 1992) and spontaneous trait inferences (Uleman et al., 2008), it can be expected that people will form impressions of social others even from minimal cues and exposure. However, to date, there had been no data on the extent and type of information users infer solely on the basis of browsing social media. The first objective of my dissertation is to establish an operational definition of ambient awareness, grounding it in relevant notions from psychology and computer-mediated communication and to provide empirical data on primary questions related to its prevalence and content.

Aspects of the definition of ambient awareness imply that the process is automatic (i.e., it is cognitively efficient and occurring spontaneously). The question of automaticity is crucial, considering the large amount of information on social media and networking sites. Processing this information without particular effort and deliberation can be key to deriving benefits from online social networks. There is consistent evidence that trait inferences are made spontaneously on the basis of minimal cues, such as short behavioral descriptions or brief exposure to faces and non-verbal behavior (Uleman et al., 2008). However, as discussed earlier, the extent to which spontaneous trait inferences are made on social media is not clear because (a) microblogging updates are self-generated; (b) multiple updates are viewed simultaneously; (c) updates are not processed attentively but are viewed in 'browse mode'. Therefore, the second objective of my dissertation is to test whether people make spontaneous inferences when browsing social media.

Lastly, crucial to information exchange is awareness of who knows what. Inferences of expertise are different from trait inferences. The explanation behind spontaneous inferences in psychology revolve around the idea that some information is inherently and fundamentally valuable (Moskowitz & Olcaysoy Okten, 2016; Uleman et al., 2008). For example, knowing others' traits and goals helps people judge whether they would attack or protect them, which is likely not the case when it comes to knowing whether someone is a programmer or a photographer. My third objective is to test whether inferences of domain expertise occur spontaneously.

# 2. Exploring ambient awareness

In a set of exploratory surveys, I sought to establish an operational definition of ambient awareness and gather evidence regarding its occurrence among social media users. To examine whether awareness of online contacts can develop peripherally from browsing social media, the surveys were conducted among users of the microblogging site Twitter. Individual posts on Twitter are limited to 140 characters and posts are typically public. Communication on the site takes place via brief posts and ambient awareness can be studied in the relative absence of more extensive forms of communication.

## 2.1 Method overview

Data about each participants' own Twitter network were retrieved automatically via Twitter's API. Participant saw a list of 100 randomly selected people whose updates they followed on Twitter and were asked to classify as many as possible and at least 50 into (a) people they encounter primarily on Twitter (Twitter-only contacts); (b) people they encounter outside of Twitter; (c) non-human, that is, corporate accounts, brands, promoter, spam, or other automated services; (d) unknown, in case they could not at all recognize the account. This Twitter Network Survey procedure allowed for assessing participants' awareness towards people they knew only through Twitter. For a random selection of Twitter-only contacts, participants answered a number of questions starting with familiarity ("Are you at all familiar with this person?") and probing further into what they knew about the user (checklist of common person-information categories, such as hobbies and interests, major life events), expertise awareness (checklist of common recreation activities and professional sectors), passive communication (frequency of seeing posts) and active communication (direct messages and reacting to content), relationship duration, and perceived competence and approachability.

The surveys also featured a single-item assessment of participants' experience of ambient awareness based on the following definition: "It is possible that when using Twitter, you develop awareness of the people whose updates you follow. Even if individual updates are short and mundane, together they might give you an idea of the person who posts them - what they are like, what they do, etc. Do you experience such general awareness of the people in your Twitter network and to what extent?" It was rated on a continuous scale from 1 (not at all) to 10 (to a great extent).

The surveys were conducted online with a convenience sample of US citizens from the online panel Tellwut (tellwut.com). Study 1 had a sample of 213 participants (56% women). The average network size was 427 (*SD* = 608; Mdn = 135) and the average duration of Twitter use was 3.5 years (*SD* = 2). Study 2 had 148 participants (68% female), mean network of 519 (*SD* = 634; Mdn = 217) with 4 years (*SD* = 2) average duration of Twitter use.

## 2.2 Main Results

The majority of participants reported moderately high levels of awareness for people in their Twitter network (Study 1: $M$ = 5.65, $SD$ = 2.09; Study 2: $M$ = 6.32, $SD$ = 2.25), indicating that experiencing ambient awareness was not uncommon in a diverse sample of Twitter users. Awareness was not only a general experience. When participants saw the profiles of people they follow on Twitter, they reported being familiar with a substantial proportion of these profiles.

Roughly half of the presented profiles were recognized (46% in Study 1; and 63% likelihood in recognizing a profile in Study 2), which is substantial, considering the large average network size in the studies. For each person identified as at least somewhat familiar, participants answered whether they knew the person outside of Twitter. A large number of people were only known through Twitter (75% in Study 1 and 73% in Study 2). Furthermore, passive communication, that is, frequency of encountering a persons' posts, was the best predictor of individual-level awareness ($B$ = 0.36, $SE$ = 0.06, $p < .01$), even while controlling for relationship duration ($B$ = 0.07, $SE$ = 0.05, $p > .05$), and

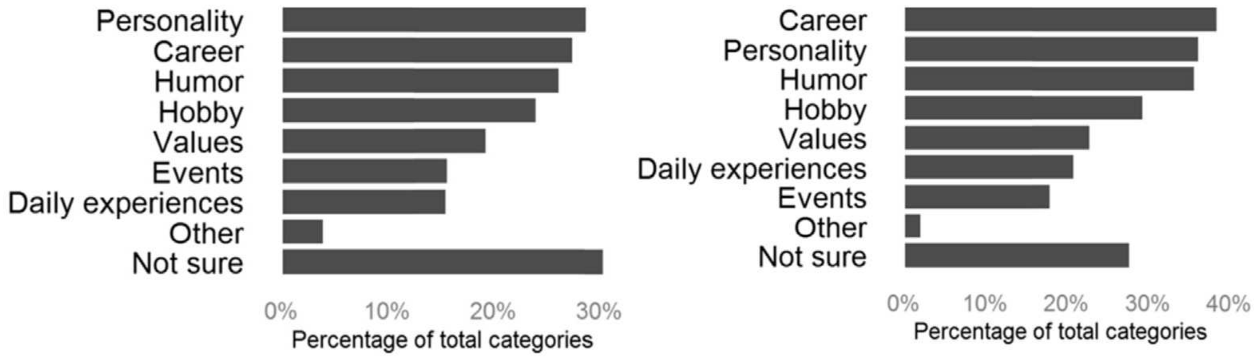


Figure 2.1: Distribution of information categories in Study 1 (left) and 2 (right). Checklist measure. Reproduced from Appendix A Figures 1 and 2.

active communication ($B$ = 0.21, $SE$ = 0.09, $p < .05$). Together, these findings suggest that ambient awareness can develop from reading microblogging content.

Awareness was not merely a general, undifferentiated experience. Instead, participants were able to report the kind of information they had encountered about individual members of their network. The most commonly reported categories were information about the target's personality, career, humor, and hobbies. Individual frequencies can be seen in (Figure 2.1). The number of reported knowledge categories was positively associated with ambient awareness (r = .59, $p < .001$).

## 2.3 Discussion

The two surveys revealed that social media users experience ambient awareness. The users' subjective experiences were complemented by their ability to recognize and report specific knowledge of people they follow on Twitter, but had not met in real life. These results strongly suggested that microblogging posts are sufficient for ambient awareness to develop. Hence, the first project of my dissertation served to highlight the likely existence of the phenomenon of ambient awareness and justify its further investigation.

# 3. Spontaneous inferences online

The second aim of my dissertation was to investigate whether spontaneous trait inferences occur under conditions characteristic of social media and networking sites: non-extreme, ostensibly self-generated content (Experiment 1), simultaneous presentation of multiple cues (Experiment 2), and self-paced browsing (Experiment 3). I adapted an established social-cognitive paradigm, which assessed inferences indirectly via a probe recognition task, while ruling out the effects of memory and intentionality. This project included two additional experiments (1A and 2A), which were conceptually similar of Experiments 1 and 2 and yielded very similar results. To avoid redundancy and comply with a strict word limit, I wrote a paper based on the three main experiments and reported the remaining ones in a supplementary report (Appendix C).

## 3.1 Method overview

All experiments were based on an adapted version of the false recognition paradigm (Todorov & Uleman, 2002), where inferences are assessed via a probe recognition task. First, participants saw a number of social media posts, consisting of sentences and realistic pictures of actors who ostensibly posted them. Some of the sentences implied traits (e.g., "Just spilled coffee all over my laptop" implying clumsy). Participants were asked to read the posts without any mention of impression formation (learning phase). In Experiment 1, status updates were presented one at a time for 5 seconds. In Experiment 2 there were 9 updates per trial. In Experiment 3, all updates were presented on a timeline, which participants could browse at their own pace, while instructed to select the updates they find interesting.

In a subsequent recognition task, the same actors were paired with single words, and for each pair participants indicated whether the word appeared in the actor's description. It has been shown that if the target word is the trait implied by the actor's description, participants make more mistakes saying that it was in the description (Todorov & Uleman, 2002). This false recognition of implied traits occurs because, while reading the descriptions, participants spontaneously infer the implied traits and associate them with the corresponding authors. Hence, false recognition rates serve as a dependent variable and a pattern where more recognitions are made on same-trait trials is interpreted as support for spontaneous trait inferences.

In addition to the established false recognition measure, I introduced alternative assessments of impression formation, which involved choosing traits to describe an actor (Experiments 1 and 2) and choosing between two actors for a scenario that calls for the trait implied for one of the actors (Experiment 3).

The experiments were conducted in a lab, with a convenience sample of undergraduate students recruited from the participant pool of a German research institute. For five within-subject experiments the sample was 169 participants.

## 3.2 Main Results

The primary dependent variable - false recognition rates - was analyzed with paired-sample t-tests. In all of the experiments, I tested whether participants made more mistakes for same-trait trials as compared to control trials.

Thirty participants took part in Experiment 1 (22 female). Participants made more mistakes when an actor's face was paired with the trait implied by this actor's post (implied-trait condition; $M$ = 0.55, $SD$ = 0.24), as compared to a trait implied for another actor (other-trait condition; $M$ = 0.34, $SD$ = 0.22, $p < .001$, Hedges' g [95% CI] = 0.89 [0.41, 1.4]) or a novel trait (control condition; $M$ = 0.23, $SD$ = 0.17, $p < .001$, Hedges' g [95% CI] = 1.47 [0.89, 2.13]). This pattern suggests that people spontaneously inferred traits when reading status updates with mild content, written from a first-person perspective.

Results from the impression formation measures were analyzed with exact binomial tests. The results from the impression formations measure were analogous: When asked to evaluate the actors from the learning task, participants selected the implied trait over another trait of the same valence 62% of the time. An exact binomial sign test indicated that this was significantly higher than chance (95%CI [0.55,0.69], $p$ = 0.001).

Nineteen participants took part (16 female) in Experiment 2. Multiple actors were presented simultaneously, which is why the experiment featured different control conditions. Same-trait trials were compared to trials where an actor was presented with the trait of another actor who had originally appeared in the same trial (other trait, same trial) or in a different trial (other trait, other trial). Participants made considerably more mistakes when an actor's face was paired with the trait implied for this actor (implied-trait condition; $M$ = 0.57, $SD$ = 0.23), as compared to a trait implied for another actor in the same trial ($M$ = 0.3, $SD$ = 0.15, $p < .001$, Hedges' g [95% CI] = 1.32 [0.75, 2]) or another trial ($M$ = 0.29, $SD$ = 0.18, $p < .001$, Hedges' g [95% CI] = 1.3 [0.67, 2.03]). There was no significant difference between the two control conditions. Crucial in this experiment is the difference in false recognitions between traits, implied by status updates that were presented during the same trial. Although the updates appeared simultaneously, the trait implied by each update was exclusively associated with the person who posted the update.

Again, the pattern emerging form the alternative assessment was consistent. When asked to evaluate an actor, participants chose the implied trait over another trait of the same valence 75% of the time, which was significantly higher than chance (95%CI [0.66,0.82], $p < .0001$). These results provide evidence that participants made actor-specific trait inferences.

Experiment 3 had all status updates presented on a single timeline, which participants browsed at their own pace. There were forty-five participants (37 female). Here the control conditions were the same as in Experiment 1: the trait of another actor or another trait. The pattern of means was consistent with previous findings: higher number of error rates in the implied-trait condition ($M$ = 0.43, $SD$ = 0.25), as compared to other-trait ($M$ = 0.37, $SD$ = 0.21, $p$ = .058, Hedges' g [95% CI] = 0.28 [0.01, 0.57]) and control ($M$ = 0.24, $SD$ = 0.19, $p <.001$, Hedges' g [95% CI] = 0.86 [0.5, 1.24]). The difference between implied and other-traits was small and only approaching significance. Given that the means were in line with the hypothesis and a one-sided test (justified by the preregistered directional prediction) would have been significant, my conclusion is that spontaneous inferences did occur.

This experiment featured a scenario-based assessment of impressions where participants had to choose between two actors for a scenario that calls for the trait implied for one of the actors. Across four different scenarios, participants selected the actor whose status update implied a trait that would be desirable in the particular scenario 61% of the times, which was significantly higher than chance (95%CI [0.54,0.68], $p = 0.002$), which offered support for the occurrence of trait inferences.

Throughout all experiments, I assessed participants memory for the stimulus materials and established that their recall was low. Responses were mostly absent (40% - 47%) or highly inaccurate (28% to 41%). Occasionally, participants recalled the sentence of a different actor from the dataset (16% - 18%). More details can be found in Appendix B.

## 3.3 Discussion

The experiments showed that trait inferences occur from non-extreme self-generated content, which is commonly found in social-media updates (Experiment 1) and when 9 status updates from different people were presented in parallel (Experiment 2). Although inferences did occur when participants browsed freely, the results cast doubt on whether participants successfully associated the traits with the corresponding status update authors (Experiment 3). Visual summary of the results can be seen in Figure 3.1.

A major strength of this project was bringing together research on snap social judgment and online impression formation. Prior research has shown that person-inferences are unintentional, cognitively efficient, long-lasting, and can be of traits, but also values, goals, or intentions (Uleman et al., 2008). That similar process takes place on social media where information is often merely glanced at, is the main line of reasoning behind of ambient awareness (Leonardi, 2015; Leonardi & Meyer, 2015; Thompson, 2008; Utz, 2016), but this project is the first to directly address and demonstrate it. The project was a crucial step towards examining the impact of spontaneous impression formation on

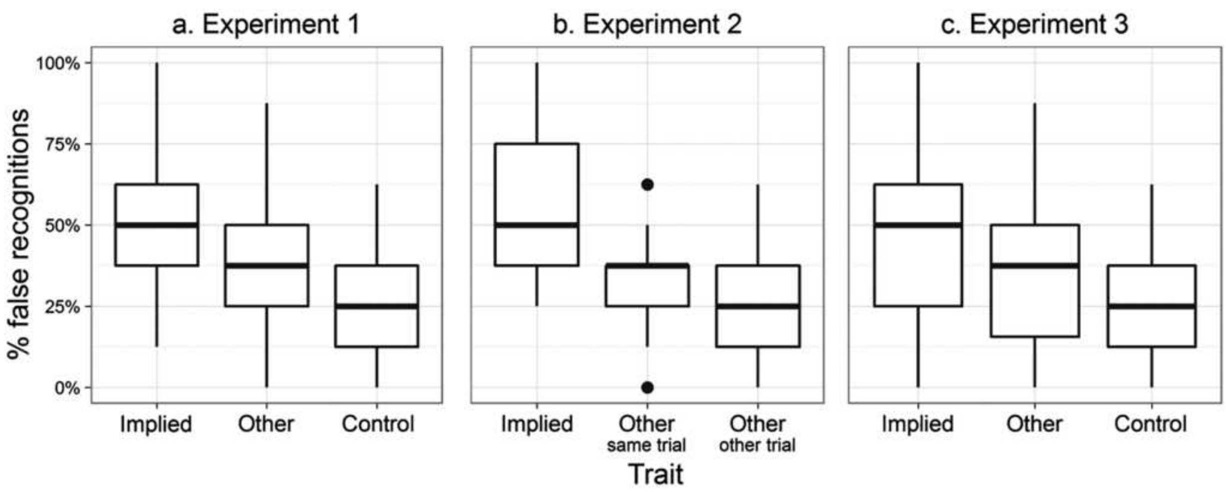


Figure 3.1: Visual summary of results from the false recognition paradigm. Higher number of false recognition rates in the implied-trait condition (relative to the other two conditions) indicate occurrence of spontaneous inferences. Center lines show the medians; box limits indicate first and third quartiles; whiskers extend to the highest and lowest value within 1.5 times the interquartile range; outliers are represented by dots. Reproduced from Appendix B Figure 2.

relational and informational processes online. One limitation of the project were the inconclusive results with regard to self-paced browsing. Although present, evidence for spontaneous inferences during browsing was weaker and I sought to validate it further in the subsequent studies I conducted.

# 4. Spontaneous inferences of expertise

The purpose of this project was to examine whether awareness of domain expertise (who knows what) can develop spontaneously and efficiently in the course of browsing. Although there is evidence that spontaneous inferences are made for various kinds of information, including traits, goals, and values, the explanations behind spontaneous inferences revolve around the idea that some information is inherently and fundamentally valuable (Moskowitz & Olcaysoy Okten, 2016; Uleman et al., 2008). For example, knowing others' traits and goals helps people judge whether they would attack or protect them, which is likely not the case when it comes to knowing whether someone is a programmer or a photographer. I therefore pursued this question in a set of online experiments.

## 4.1 Method overview

The experiments in this project were also based on the false recognition paradigm. Participants (observers) browsed social media posts, some of which contained cues to the expertise of the people who ostensibly posted them (actors). Instead of implying traits, some posts contained domain cues (e.g., "Front-end developer aka JavaScript wizard also HTML5/CSS3. Hire me!" suggesting knowledge in programming). The focus of the first experiment was on whether people infer domains (as opposed to traits). Participants were asked to read the posts and saw either one post per trial or browsed all posts on a timeline. Thus, this experiment included a presentation condition where I had previously found strong evidence for spontaneous trait inferences (single posts) and a condition in which the results with regard to traits were inconclusive (timeline). In the second experiment, all participants saw the posts on a timeline and were only instructed to browse though the posts, rather than read them. The purpose was to test whether domain inferences persist when attentiveness is diminished. Two additional factors were introduced: half of the actors appeared had only one domain cue and the other half had four domain cues (number of domain cues; within-subjects); some participants received instructions which increased the salience of domain knowledge by implying an upcoming expert selection task (implied goal; between-subjects).

To avoid potential confounds related to participants' stereotypes of certain domains, I used an algorithm to generate a novel set of stimuli on each run. In this way, each participant saw a particular domain with a different combination of face, name, and sentence. There was no mention of expertise inference or impression formation in the instructions, therefore the inferences observers made can be considered spontaneous. The experiments were browser-based and closely resembled an actual social media site.

The false recognitions measure was similar to the one used in the Spontaneous Trait Inferences project, with the only difference that probe type was manipulated within and not between actors. That is, each actor from the learning phase appeared twice in the probe recognition task: once with the domain implied by their learning-phase post and once with the domain implied for another actor. In this study, I also measured domain inferences directly, by asking participants to identify the domain of each actor from a list of 9 domains and an option to skip the question. Experiment 2 included an additional measure of impressions, where participants saw pairs of actors from different within-subject conditions (single domain cue; multiple domain cues; single neutral cue; multiple neutral cues) and were asked to select the more approachable or the more competent.

The experiments were conducted online with a convenience sample recruited through the participant pool Prolific (http://prolific.ac). Most participants were employed full-time (ca. 50%), part-time or unemployed and seeking a job (ca. 30%). The final sample consisted of 91 participants in Experiment 1 and 269 participants in Experiment 2.

## 4.2 Main Results

The false recognitions measure was analyzed using linear mixed models fit by maximum likelihood (Bates et al., 2015). For the domain identification measure, observed accuracy was compared to chance-level accuracy (guessing) using binomial tests. Generally, the two measures of domain inferences revealed analogous results.

In Experiment 1, there was the predicted main effect of probe type on false recognition rates and no effect of presentation. First, to determine the effect of probe type (same versus other), we compared an intercept only model (M1) with a model including probe type (M2) and a model with interaction between probe type and presentation (M3). Participants made more mistakes on same-domain ($M$ = 0.52, $SD$ = 0.22) versus other-domain trials ($M$ = 0.39, $SD$ = 0.23; Hedges' g = 0.4 95%CI [0.11,0.7], $p < .0001$), regardless of presentation. With regard to domain identification, in both conditions, participants' responses were significantly higher than chance at recognizing the domains implied by actors' posts (single post condition: 30% of successful recognition, 95%CI [0.25,0.34], $p < .0001$; timeline condition: 33% of successful recognition, 95%CI [0.28,0.38], $p < .0001$). There was no significant difference in domain identification accuracy between the two presentation conditions, t(78) = -0.703, $p$ = 0.48.

According to the results of Experiment 2, when instructed to browse through a timeline of social media posts, participants spontaneously inferred actors' domains of interest/expertise from their posts, but only for actors who had multiple expertise-implying posts. For actors with multiple-domain cues, participants made more mistakes on trials where actors were presented with the domain implied by their posts (same; $M$ = 0.65, $SD$ = 0.29), as compared to trials on which actor were presented with other domains (other; $M$ = 0.42, $SD$ = 0.28; Hedges' g = 0.52 [0.35,0.69]). For actors with single-domain cues, participants made similar number of mistakes regardless of probe (same: $M$ = 0.47, $SD$ = 0.28; other: $M$ = 0.43, $SD$ = 0.27; Hedges' g = 0.11 [-0.06,0.28]).

The analyses of domain identification revealed a similar pattern: Participants were slightly, but significantly, better than chance at recognizing the domains of actors with a single cue (24% of successful identification, 95%CI [0.21,0.27], $p < .0001$) and substantially better for actors with multiple cues

(40% of successful identification (95%CI [0.37,0.43]), $p < .0001$). Thus trait inferences only occurred for actors who had multiple domain cues.

There was no effect of expertise salience (expertise-related goal implied by the mention of an upcoming task), but due to a failed manipulation check, it was not possible to determine whether the lack of effect was due to the irrelevance of expertise salience or to an unsuccessful manipulation.

Another finding was that the inferences participants made also colored their impressions of the actors (Figure 4.1): Actors with domain-implying posts were more likely to be judged as competent. Actors seen more frequently were generally judged as more approachable.

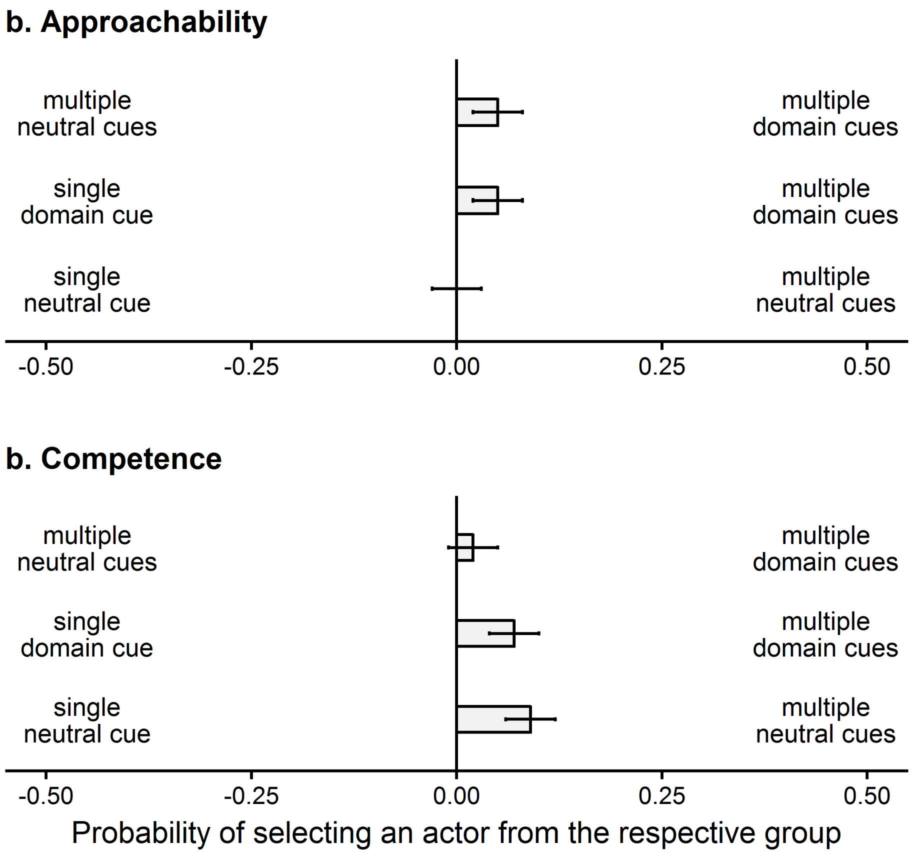


Figure 4.1: Probability of selecting an actor as more (a) approachable or (b) competent as a function of cue type (domain vs. neutral) and number (one vs. four cues). Reproduced from Appendix D Figure 4.

## 4.3 Discussion

The findings suggest that people spontaneously extract information about domains of expertise. Brief glances at posts such as “Front-end developer aka JavaScript wizard, hire me!” were sufficient for participants to infer the implied domain (‘programming’) and associate it with the person who posted the update. When participants were merely instructed to browse through a timeline of social media posts, they spontaneously inferred actors’ domains of expertise implied by the actors’ posts, but only for actors who had multiple expertise-implying posts. One interpretation of this pattern is that multiple posts resulted in stronger inferences, that is, that inferences from multiple cues were stronger than inferences from single cues. Alternatively, it is possible that participants simply skipped some of the posts. In this case, if an actors’ expertise can be inferred from multiple cues, the likelihood that a participant stumbled upon at least one of them was greater than if there was only one cue. Regardless of the underlying mechanism, our results show that people inferred the expertise of others while browsing.

Programming the experiments in a way that allowed for random pairing of stimuli on each run (e.g., for each participant having a different actor face and name assigned to being a ‘programmer’), was an important methodological innovation. Extraneous stimulus information, such as the actors’ gender and appearance are likely to trigger stereotypes. The random pairing of stimuli ensured that any potential confounding effects of stereotypes are random rather than systematic.

The main indirect measure was based on false recognitions (i.e., mistakes), thus ruling out the possibility that the effect was due to memorizing the materials. The conditions under which the effect was observed closely resembled casual social media browsing. This leads us to expect that processes of spontaneously domain recognition occur in everyday life.

# 5. General discussion

Social media have been defining of the past decade, introducing major changes to communication in personal and professional settings. The vast networks that social media help maintain and the copious influx of information are both one of their biggest advantages and one of their greatest challenges (Donath, 2007; Resnick, 2001). With a large number of contacts and easy communication, any information or referrals a person might need from others is likely at their fingertips. But to tap this potential, social media users need to solve the key challenges of locating and retrieving information. That is, at the very minimum they need to be aware of who is who and who knows what in their networks.

In my dissertation, I examined the proposition that through the constant stream of social information, the permanent browsing and reception of network updates via social media, people gain ambient awareness of their online networks, including the crucial information of who is who and who knows what. Two surveys focused on the phenomenon and its potential antecedents and consequences. The insights were promising: People not only recognized ambient awareness as something they experience online, but were also able to recognize and report information about people they had only gotten to know through browsing updates on a microblogging platform. These surveys were a clear indication that the topic is worth delving into and helped refine and ground the construct. However, they did not address the most crucial assumption of the ambient awareness – that awareness arises spontaneously, without conscious effort and deliberation. Testing this process was the main aim of my dissertation.

To test whether ambient awareness can indeed arise spontaneously, I adapted a paradigm from psychological research on spontaneous trait inferences. A series of experiments revealed that after viewing social media posts people spontaneously formed accurate impressions of the actors who had ostensibly written the posts. These impressions included traits, such as reliable or unfriendly, states, such as happy or confused, and domains of expertise, such as programmer or photographer. Another insight was that the amount of exposure and content had downstream consequences of people's impressions of competence and approachability. That people infer crucial information spontaneously while browsing social media is a premise underlying most reasoning surrounding ambient awareness and the role of social media use in information exchange and these studies are the first to directly test it.

## 5.1 Implications

Scholars have argued that finding temporally and cognitively efficient ways to maintain online networks is the key to unlocking their tremendous potential (Donath, 2007; Resnick, 2001). Several insights from my work suggest that ambient awareness might be this processes. Awareness itself is a form of social presence, which makes it a form of relational maintenance (Tong & Walther, 2011b). Several qualitative studies have described a positive association between ambient awareness and relational maintenance in personal (Cornejo et al., 2013; Ito, 2005; Romero et al., 2007) and professional contexts (Dimicco et al., 2008; Ehrlich & Shami, 2010), but little was known about the efficiency of the underlying process. One of the main conclusions of the spontaneous inferences projects I conducted is that ambient awareness is a cognitively efficient process occurring as a by-product of browsing social media posts. In conditions closely resembling social media browsing, people became more aware of the social others without being instructed to do so. Importantly, their improved awareness was not due to memorizing entire posts, but to extracting valuable information. This strongly suggests that for social media users, being permanently connected and exposed to social information (Vorderer et al., 2016) does not mean drowning in noise, but rather growing aware of their online social networks.

As to how ambient awareness can enhance knowledge exchange via social media, two processes can been envisioned: enhancing the interpersonal processes between the parties involved in the exchange and enabling transactive memory to develop within a network (Fulk & Yuan, 2013). First, improved interpersonal awareness (who is who) via trait inferences and mere exposure can make people more comfortable approaching their weak and absent ties. In the anecdotal example from the opening paragraphs, this was the case with a researcher finding it easier to approach a potential collaborator after learning about their hobbies. Several of the studies I conducted suggest that awareness can indeed make people more comfortable approaching strangers. In the exploratory surveys the association between awareness and approachability was correlational. In the experiments on trait inferences, it was the product of minimal cues suggesting that a person is friendly, and in the last set of experiments it was the mere exposure to a person's posts. As previously discussed, enhancing interpersonal relationships has broad consequences for information exchange (Leonardi & Meyer, 2015; Levin & Cross, 2004; Lu & Yuan, 2011).

Awareness of who knows what is crucial for teams and organizations, as it supports knowedge exchange and the effective coordination of tasks (Austin, 2003; Treem & Leonardi, 2015). While it is generally assumed that social media use contributes to such awareness, based on the results of my dissertation we know one underlying process is that of spontaneous inference from passive browsing. By virtue of being seamless and spontaneous, as my dissertation work suggests, ambient awareness presents an interesting alternative to knowledge repositories, which are traditionally used to enhance expertise recognition in organizations but have been criticized for not being sufficiently engaging (Hinds & Pfeffer, 2003). On a personal level, it can help people identify potential sources of information and tailor directed requests, rather than broadcast to their extended networks, which could involve disclosing sensitive information (Vitak & Ellison, 2012). Demonstrating that domain inferences and the resulting awareness of who knows what in a network occur spontaneously helps understand how social media contribute to information exchange (Chui et al., 2012; Fulk & Yuan, 2013) and is therefore a valuable contribution to communication and organization science.

Furthermore, expertise awareness is a core component of transactive memory, which remains one of the major theories of group cognition (Lewis & Herndon, 2011; Wegner, 1987). So far, close relationships and extended face-to-face communication have been the primary known antecedents (Hollingshead, 1998; Lewis, 2004; Wegner et al., 1991) and digital technologies have been used as a tool to provide awareness directly (Alavi & Leidner, 2001). The spontaneous inferences of domain expertise revealed in the last project of my dissertation present another possible antecedent of transactive memory, which is particularly relevant for computer-mediated communication, as it does not involve face-to-face communication and external repositories.

Despite its positive implications for network maintenance and information exchange, ambient awareness is not necessarily associated with well-being. On the contrary, awareness of negative life events within one's network has been linked to stress (Hampton et al., 2015). Communication with weak ties also does not carry the emotional benefits of close relationships, and can in fact have negative consequences when carried out at the expense of communication with strong ties (Burke & Kraut, 2016). Since these emotional effects are independent of informational benefits, the processes I discuss throughout the dissertation do not contradict existing findings on the negative emotional effects of passive browsing (Burke & Kraut, 2016) and the cost of caring (Hampton et al., 2015).

Demonstrating that people infer domains of expertise from short descriptions of behavior as readily and efficiently as they infer traits and values, adds to the body of work on spontaneous inferences (Uleman et al., 2008) and builds towards its conceptual understanding. The theoretical antecedents of the phenomenon are still actively discussed and explanations typically revolve around the idea that some information such as traits and goals is inherently valuable, as it helps us judge whether they would attack or protect us (Skowronski et al., 2008; Moskowitz & Olcaysoy Okten, 2016). This, however, is certainly not the case when it comes to knowing whether someone is a programmer or a photographer. The domain inferences we observed are not readily explained by evolutionary relevance. Instead, they suggest that the process of spontaneous inferences might be a product of basic information processing mechanisms of information extraction (Kintsch & Van Dijk, 1978).

### 5.1.1 Methodological innovations

For two of the projects in my dissertation I developed novel methodological approaches and made the code freely available to other researchers (http://github.com/anidroid). Network surveys are a commonly used method, in which respondents list individual members of their social network and then respond to the same set of questions for each person on the list. The Twitter Network Survey procedure I developed for the exploratory surveys allows researchers to automatically retrieve the profile information of members of the respondents' Twitter network and present these profiles along a set of questions. The procedure featured an additional stage of quick filtering of users (e.g., selecting only colleagues; excluding family members, etc.).

In the domain inferences project, I developed a browser-based task in which participants view actor-cue pairs in the form of status updates and later report impressions of the actors. The general setup corresponds to most impression formation paradigms and can be used for various research purposes. Importantly, the code allows for random pairing of stimuli (e.g., assigning a different actor to a critical cue on each run). This randomization assures that the potential confounding effects of extraneous stimulus characteristics variables are not systematically confounded with experimental manipulations. To make the code reusable, I wrote it in a way that basic knowledge of programming would allow other researchers to set it up, change the stimulus materials, and adapt the task to suit their own purposes.

## 5.2 Limitations and future directions

The role of ambient awareness in information exchange informed and inspired the present research. Particular findings, such as the spontaneous inferences of who knows what and the effect of exposure on familiarity and liking, carry direct implications for information exchange processes. Familiarity and awareness of who knows what are known to facilitate information exchange. Still it would be important to combine these insights and study the effect of ambient awareness on information-related tasks within a coherent paradigm. One important consideration is that the effects of ambient awareness would ultimately depend on its content. Although the effects of expertise awareness on knowledge exchange are generally positive (Austin, 2003; Lewis & Herndon, 2011), in certain conditions they can undermine people's willingness to share (Ray et al., 2012). The role of content is independent of the processes through which awareness arises and calls for a separate line of research, for which my thesis dissertation work provides a solid foundation and suitable paradigms.

The accuracy of ambient awareness is a broad and interesting topic. In the experiment on spontaneous inferences, accuracy was understood as correspondence between the content of a cue and a subsequent impression. Whether and when social media posts provide accurate information about the people who post them is a question of cue validity and is relevant for some but not all proposed functions of ambient awareness. Deciding to approach an unfriendly person, because of mistakenly assuming they are helpful might still result in receiving the needed piece of advice or information. On the other hand, deciding to disclose sensitive information to someone who appears trustworthy but in fact is not, can incur serious costs. These examples serve to illustrate that albeit relevant, the question of cue validity is separate from ambient awareness.

A related issue is that of domain knowledge versus actual competence. In the domain inference experiments, the conceptualization of expertise was in terms of domains rather than degree of competence. This conceptualization is close to the notion of knowing who knows what in order to find potential sources of information or referrals, and therefore of primary interest to us. Competence is critical for particular aspects of the information exchange process (e.g., judging the credibility of received information) and for other tasks such as expert selection. It demands further investigation. Future research could consider the digital footprints of high and low competence (e.g., linguistic markers, endorsements) and whether people can reliably identify them, either spontaneously or deliberately.

The experiments I conduced showed that people spontaneously infer key information about others. I used materials designed to contain certain types of information (traits and domains of expertise). Quantifying the type of content that an actual social media user is exposed to over time can be crucial to understanding their experience of ambient awareness. For example, the effect of frequency of browsing social media on awareness of who knows what might be moderated by the number of domain-related posts a person has encountered. Due to the large influx of information on social media, standard content analysis would not be feasible and automated computational approaches might be necessary.

# 6. Conclusion

Through social media, people are constantly exposed to a stream of social updates and notifications from their vast online networks. The bits of information to which people rarely devote more than a passing glance can easily be seen as meaningless noise. The present research suggests otherwise. Passive browsing of brief posts contributed to people's awareness of others' traits, activities, and areas of expertise. It is therefore likely that by browsing social media, people can grow aware of their online contacts even while merely ticking off notifications and distractedly scrolling through newsfeeds. The implications of this process are substantial. With the lightweight cost-efficient means of communication afforded by social media, all information that social media users could possibly need is likely at their fingertips. Awareness can help people access this information. This dissertation lays the foundation of understanding ambient awareness and its role in online social networks.

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# Appendix A

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# Ambient awareness: From random noise to digital closeness in online social networks

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ABSTRACT

Ambient awareness refers to the awareness social media users develop of their online network in result of being constantly exposed to social information, such as microblogging updates. Although each individual bit of information can seem like random noise, their incessant reception can amass to a coherent representation of social others. Despite its growing popularity and important implications for social media research, ambient awareness on public social media has not been studied empirically. We provide evidence for the occurrence of ambient awareness and examine key questions related to its content and functions. A diverse sample of participants reported experiencing awareness, both as a general feeling towards their network as a whole, and as knowledge of individual members of the network, whom they had not met in real life. Our results indicate that ambient awareness can develop peripherally, from fragmented information and in the relative absence of extensive one-to-one communication. We report the effects of demographics, media use, and network variables and discuss the implications of ambient awareness for relational and informational processes online.



## 1. Introduction

"What is happening right now?" is a question social media and networking sites constantly ask their users. The typically brief answers are then broadcasted to large audiences, often a person's entire network on the given site. At the same time, people receive and skim through updates from friends, relatives, acquaintances, or even strangers. This type of communication is perhaps best characterized by the incessant flow of brief and mundane bits of information. Closely linked to the ubiquity of social-networking sites and mobile devices that allow people to be permanently online and connected, such incessant mediated communication is unprecedented and scholars are yet to understand its interpersonal effects (Vorderer & Kohring, 2013). One intriguing possibility is that even if individual updates are brief and mundane, continuously receiving fragments of personal information can result in ambient awareness of what is going on in the lives of people who post them. Science writer Clive Thompson was the first to propose how ambient awareness can develop in the context of public social media sites, such as Facebook and Twitter (Thompson, 2013). Ambient awareness can be defined as awareness of social others, arising from the frequent reception of fragmented personal information, such as status updates and various digital footprints, while browsing social media. "Ambient" emphasizes the idea that the awareness develops peripherally, not through deliberately attending to information, but rather as an artifact of social media activity. Central to this definition is that browsing social media is sufficient for awareness to develop, even in the absence of directed communication.

Prior research has looked into existing social networks, which afford directed communication (e.g., Facebook; Lampe, Ellison, & Steinfield, 2006), making it difficult to single out the contribution of mere browsing. Several scholars have considered ambient awareness, also referred to as *peripheral* or *pervasive awareness*, and its potential role in relational maintenance (Lampe et al., 2006; Resnick, 2001; Zhao, Rosson, Matthews, & Moran, 2011) and organizational knowledge exchange (Dimicco et al., 2008; Leonardi & Meyer, 2014; Zhao et al., 2011). However, the construct has been discussed primarily in theoretical terms and described qualitatively, without being empirically assessed.

In the present research, we sought to establish an operational definition of ambient awareness, grounding it in relevant notions

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from computer-mediated communication (CMC) and psychology and to provide empirical data on primary questions related to its occurrence and functions.

## 2. Theoretical background

In face-to-face encounters, people naturally develop awareness of others by picking up on non-verbal cues. Co-workers who share the same office, for example, get a sense of each-other's daily moods and activities. Co-presence enhances communication by increasing familiarity and providing people with information. In mediated communication there is no physical presence, but a sense of social presence (i.e., quality of "being there") and awareness can nevertheless emerge (Tu & McIsaac, 2002; Walther & Bazarova, 2008).

We expect that browsing social media posts can also contribute to a sense of awareness of the people who post them (ambient awareness). A major difference from prior work is that browsing social media is a passive, non-directed activity. In contrast, the majority of research on social presence has focused on active, interpersonal communication (e.g., Gunawardena & Zittle, 1997; Walther, 2007). Since browsing is often done distractedly, ambient awareness is rather a product of automatic social processes, such as spontaneous inferences (Ambady & Rosenthal, 1992; Uleman, Adil Saribay, & Gonzalez, 2008), than of deliberately trying to get to know a person, for example through active, communication, information seeking, or mentalizing. We know from psychological research that people form impressions about social others after very brief exposure to minimal content, even without intention or awareness of doing so (Uleman et al., 2008; for a review). Person-judgments are spontaneous and ubiquitous and it is therefore likely that they occur during browsing. In addition to specific impressions, the mere exposure to people's posts might lead to greater familiarity (Bornstein, 1989; Moreland & Zajonc, 1982).

### 2.1. Prevalence and content of ambient awareness

Whether ambient awareness indeed develops on public social media sites, remains to be established. In qualitative studies of enterprise social media, that is, company-intern social media, people have reported experiencing ambient awareness towards their colleagues (Zhao et al., 2011). Although informative and compelling, these subjective accounts do not provide evidence as to whether awareness is actually present. That is, it is not clear whether people are indeed aware of their online contacts or merely experience a sense of awareness, but will not be able to recognize individual members of this network. Similar problem is reflected in research, where feature use (e.g., reading comments) is considered a proxy for ambient awareness, but ambient awareness itself is not measured (e.g., Leonardi & Meyer, 2014). Another problem is that enterprise social media are different from public social media, in that people use them in a work-related context, usually with the intention to get to know or keep in touch with their colleagues. Such clearly defined context and purpose of use are not necessarily present on public social media sites, such as Twitter and Facebook, where use motivations and network composition are far more diverse. Lastly, most social media platforms offer ways of active communication (e.g., private chats and messaging), which makes it difficult to claim that any increase of awareness and familiarity is due to mere browsing (ambient awareness).

To gain insight into whether ambient awareness can develop in the relative absence of extensive, one-to-one communication, we focused on the microblogging site Twitter, where content is restricted to 140 characters and usually broadcasted to large audiences, rather than directed towards specific individuals. Thus our first research questions are:

**RQ1a**. Do people experience ambient awareness from browsing a microblogging site (Twitter), in the relative absence of one-to-one communication?

**RQ1b**. Is ambient awareness just a general sense of knowing, or does it involve recognizing individuals who are known primarily through social media?

Provided that people are indeed able to gain awareness of social others based on social media exposure, it is important to assess what kind of information they gain. The content of social information is crucial for understanding its consequences.

**RQ1c**. What specific information do social media users have about their online-only contacts?

### 2.2. Media use and relationship duration

We further set out to explore how ambient awareness relates to media use. Network size and frequency of use influence the likelihood of stumbling upon the posts of a particular user and is therefore relevant to ambient awareness. According to the theory of electronic propinquity (Walther & Bazarova, 2008), a sense of closeness in mediated communication develops more readily when people have experience with the medium they are using. Ambient awareness should therefore be higher for experienced social media users. We consider duration and frequency of social media use as indicators of experience.

**RQ2a**. What are the effects of network size and media use on the general experience of ambient awareness?

Whether one would develop awareness for a specific individual is likely influenced by how frequently one stumbles upon information about this person. Awareness should therefore be related to frequency of reading a person's posts (passive communication). While active communication can be expected to contribute to ambient awareness, important in our conceptualization is that active communication is not imperative and that awareness can be develop in its absence. Relationship duration is another relevant factor. The social information processing theory (Walther, 1996) would predict that extended periods of time and interaction are needed for awareness to develop, whereas psychological theories on impression formation (Uleman et al., 2008) would suggest that short exposure is sufficient.

**RQ2b**. How is ambient awareness of individuals influenced by passive exposure to content, active communication, and relationship duration?

### 2.3. Role in interpersonal relationships and information exchange

Enhancing awareness in mediated environments has been associated with positive effects on relationships in both personal (Cornejo, Tentori, & Favela, 2012; Ito, 2005; Liechti & Ichikawa, 2000; Romero et al., 2007) and professional context (Dourish & Bellotti, 1992; Gross, Stary, & Totter, 2005; Liechti & Ichikawa, 2000). Similarly, social media activity can help people form awareness of their online network in a subtle, unobtrusive way.

Some evidence for the relational significance of ambient awareness comes from qualitative studies on enterprise social media. Employees who use enterprise social media have described developing ambient awareness of their colleagues, which in turn had a positive impact on relationships and information sharing (Dimicco et al., 2008; Ehrlich & Shami, 2010; Zhao et al., 2011). A recent study showed that participants who followed a person's activity on an enterprise networking site were more satisfied with subsequent information transfer from this person (Leonardi & Meyer, 2014).

According to the idea of ambient awareness, people pick up on information about social others while browsing, which resembles informal communication. Informal communication contributes to establishing common ground (e.g., Duck, Rutt, Hoy, & Strejc, 1991); Zhao et al., 2011), thereby making it easier to approach a person (Ellison, Steinfield, & Lampe, 2011). Apart from serving as a conversation starter, information about people's hobbies and profession can serve as an indication of what they are knowledgeable about. Ambient awareness can thus help social media users identify potential sources of information (Leonardi, 2015).

Understanding the role of ambient awareness in relational maintenance and information exchange is beyond the scope of this paper. However, determining whether browsing social media influences perceptions of approachability and provides knowledge of competencies is an important first step.

**RQ3a**. Does ambient awareness contribute to perceptions of approachability?

**RQ3b**. Do social media users develop awareness of their online-only contacts' hobbies and interests, including professional interests?

To address these research questions, we conducted two surveys among users of the microblogging site Twitter and developed a Twitter Network Survey procedure to assess awareness of specific individuals in participants' online network. Twitter was chosen because of the large proportion of strangers and weak acquaintances in personal networks, which allowed us to minimize the effects of prior acquaintanceship and alternative means of communication. Furthermore, content on Twitter is primarily in the form of brief posts, ambient awareness can be studied in the relative absence of more extensive forms of communication.

## 3. Study 1

### 3.1. Methods

#### 3.1.1. Twitter network survey procedure

Participants provided informed consent and temporary access to their Twitter account information. We displayed a list of 100 randomly selected people they follow on Twitter and asked them to classify as many as possible and at least 50 into (a) people they encounter primarily on Twitter (Twitter-only contacts); (b) people they encounter outside of Twitter; (c) non-human, that is, corporate accounts, brands, promoter, spam, or other automated services; (d) unknown, in case they could not at all recognize the account.

A questionnaire followed, in which we assessed participants' experience of ambient awareness, along with social media use. For the second part of the questionnaire, we displayed individual profiles (name, Twitter handle, and a profile photo) of people, whom the participants had previously classified as Twitter-only contacts. Displaying one profile at a time, we asked participants whether they knew the targets at least somewhat or not at all. When a target was at least somewhat known to the participant, a number of questions about this particular target followed. The presentation of targets (maximum 17) stopped after the participant was able to recognize and respond to questions about 5 targets. At the end, participants provided basic demographic information. They were debriefed and reimbursed. Simultaneously, we used the authentication provided by the participants to request their public data from Twitter's API. Additional Twitter data were collected through separate API requests and manual coding of profiles.

#### 3.1.2. Participants

The survey was conducted online. US citizens were recruited from an online panel (tellwut.com) and reimbursed according to the panel's standards (2$). Of the 233 initial respondents, 17 were excluded because of failing an attention check, two dropped out of the questionnaire, and one was excluded because of having an account in Twitter for less than half a week prior to the study. The final sample consisted of 213 participants (56% women), with 49% being between 18 and 34 years, 36% between 35 and 54, and 15% over 54 years. The majority of participants were employed (41%), self-employed (11%), or looking for work (6%). Homemaker was another majorly represented category (16%), followed by students (9%), unable to work (9%), and retired (6%). After excluding one outlier, the average network size was 427 ($SD = 608$; $Mdn = 135$) and the average duration of Twitter was 3.5 years ($SD = 2$).

#### 3.1.3. Materials

**General ambient awareness**: **Experience**. The experience of ambient awareness towards the network in general was assessed with a single item: “It is possible that when using Twitter, you develop awareness of the people whose updates you follow. Even if individual updates are short and mundane, together they might give you an idea of the person who posts them - what they are like, what they do, etc. Do you experience such general awareness of the people in your Twitter network and to what extent?” It was rated on a continuous scale from 1 (not at all) to 10 (to a great extent). The definition of ambient awareness used in the item was based on Thompson(2013) and refined in a qualitative pretest. In the pretest, we started with a more detailed description, featuring examples. Following participants' feedback that the described phenomenon is sufficiently clear without the additional clarifications and examples, we shortened the definition.

**General ambient awareness**: **Number of people**. Participants were asked to estimate roughly how many people they have gotten to know through posts and status updates. The answer scale ranged from 1 (several people) to 5 (almost everyone) and included a sixth, non-applicable, option.

**Awareness of individual targets**. During the survey procedure, we displayed a maximum of 17 people they followed on Twitter and asked participants whether they recognized individual profiles. This was assessed with a single item: Are you familiar with this person, ranging from 1 (not at all familiar) to 5 (very familiar). More specific questions followed for the targets who were identified as being at least somewhat familiar (answers 2 through 5).

**Network**, **media use**, **and demographics**. Relationships on Twitter are asymmetric, that is, a user can follow somebody's activities without being followed back, networks consist of (a) followers, that is, people following a user or and (b) friends, people the user follows. Being interested in the awareness users have of the people they followed, we used the latter as an index of network size. Time since registering on Twitter (in months) was used as a measure of duration. The frequency of Twitter use and general social media use were assessed on a 7-point scale ranging from 1 (*once a year or less*) to 7 (*several times a day*). Basic demographic information (gender, age, employment status) was collected. Age was measured on a categorical scale (18–24 years, 25–34 years, 35–44 years, 45–54 years, 55 years and over).

**Information categorie**s. The information participants had for each target was assessed with a checklist of common person-information categories (e.g., hobbies and interests, major life events) and asked the participants to select all categories that represent what they have gotten to know about each target. For expertise awareness, we showed lists of common recreation activities and professional sectors and asked participants to select the ones that describe the given target's hobbies and profession, respectively. All checklist variables (information categories and expertise awareness) included the options other (open-ended), not sure, and no idea.

**Approachability**. Participants reported the extent to which they find a target to be “approachable (friendly)” on a continuous scale from 1 (not at all) to 10 (extremely). The term friendly was added to clarify that approachability refers to the target's personality (i.e., warmth, friendliness) rather than availability (i.e., having enough time).

**Attention check**. Towards the end of the questionnaire we included a modified version of an instructional manipulation check (Oppenheimer, Meyvis, & Davidenko, 2009), to see whether the participants were attentive.

### 3.2. Results

#### 3.2.1. Ambient awareness (RQ1)

The majority of participants reported moderately high levels of awareness for people in their Twitter network ($M = 5.65$, $Med = 6$, $SD = 2.09$), indicating that experiencing ambient awareness was not uncommon in a diverse sample of Twitter users. To the question of estimating how many people they have gotten to know mainly through social media, the majority of responses (69%) were between few and more than several people, but less than half of the network. Awareness was not only a general experience. The majority of people (80%) were able to recognize at least 5 targets within a maximum of 17.

About half of the presented profiles (46%) were recognized, which is a substantial number, considering the large network sizes in the sample. For a selection of people identified as at least somewhat familiar, we asked participants whether they know each person outside of Twitter. A large number of people were only known through Twitter (75%). Together, these findings strongly suggest that ambient awareness can develop based on microblogging content.

#### 3.2.2. Ambient awareness of individual targets

Using the Twitter Network Survey procedure, we selected individual people from participants' own networks (targets). Targets with close relationship to the participants (i.e., family, close friends, and friends; 11%), were excluded from the analyses involving awareness. Of the remaining targets, 14% were identified as *very familiar*, 20% as *familiar*, 37% as *somewhat familiar*, and 28% as *not entirely unfamiliar.*

#### 3.2.3. Information about individual targets

Participants were able to report the kind of information they had encountered about individual members of their network. The checklist measure allowed for multiple information categories per target. Participants reported an average of two information categories per target. The category other was used only 2% of the time, which led us to conclude the list of categories was sufficiently comprehensive. The most commonly reported categories were information about the target's personality, career, humor, and hobbies (Fig. 1).

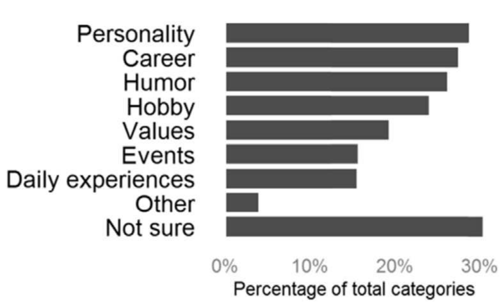


**Fig. 1.** Distribution of information categories in Study 1. Checklist measure; multiple categories per target were possible.

One type of information with particular relevance to information processes is expertise awareness, that is, awareness of who knows what in one's network. Our study included a measure, where participants indicated what a target's hobbies and profession were. The options *no idea* and *not sure* were available. Frequency analyses revealed that expertise awareness was common in the present sample. Some knowledge of targets' hobbies, profession, or both was reported for 67% of the targets.

#### 3.2.4. Demographic, network, and media use variables (RQ2)

Linear models were used to assess whether general ambient awareness and awareness of individual contacts varied across demographic groups and network characteristics. In separate models, each awareness variable was regressed on gender, age (as continuous; centered), frequency of use, network size, and time since registering on Twitter. Originally, we intended to include Twitter use as predictor, but the measure was highly skewed: 74% of all participants indicated using Twitter several times a day, which was the highest scale point. We therefore included the more normally distributed general social media use instead. Full models including all interactions were tested and whenever a simple model was not significantly different from or superior (higher Adjusted R-squared) to its complex counterpart, the simpler model is reported.

Model summaries can be seen in Table 1a. Frequency of media use was associated with both indexes of ambient awareness. Participants who used social media more frequently reported experiencing ambient awareness to a greater degree and were more likely to recognize the profiles of people from their Twitter network. Network size was negatively associated with the likelihood of recognizing individual contacts, but not with the experience of general ambient awareness. That is, people's general experience of ambient awareness did not seem to depend on the size of their network but people with large networks recognized fewer individual members of their network.

### 3.3. Discussion

The results of this study show that people experience a sense of ambient awareness towards their online network. More importantly, they were able to recognize and report information about individual people in their network, whom they know only through the microblogging platform Twitter. This awareness of individual online contacts suggests that ambient awareness is not only an illusory feeling, but that people are indeed aware of what is going on in their network. Consistent with the theory of electronic propinquity, ambient awareness was higher for frequent Twitter users. There was also an effect of age, such that older participants reported higher ambient awareness. Lastly, network size did not relate to the general experience of awareness, but seemed to be negatively associated with awareness of individual contacts.

Overall, Study 1 offers valuable insights into ambient awareness. However, it is a first, exploratory study and we cannot be certain whether the observed patterns are reliable. Furthermore, there were certain limitations. The survey procedure did not allow for precisely calculating the proportion of recognized targets, because the survey stopped after 5 targets were recognized as being at least somewhat familiar. Another problem was the scale for measuring Twitter use, which resulted in a highly skewed variable.

We therefore conducted a second study to strengthen the conclusions of Study 1 and address some of its limitations. The study kept mostly identical in order to provide additional support for the exploratory findings of Study 1.

**Table 1**
Relationship between ambient awareness, demographics, and network variables.

| | a. Study 1 | | b. Study 2 | |
|---|---|---|---|---|
| | General ambient awareness | Ambient awareness of individuals | General ambient awareness | Ambient awareness of individuals |
| Gender | 0.01 (0.07) | 0.03 (0.07) | 0.01 (0.08) | 0.04 (0.08) |
| Age | 0.10 (0.06) | 0.20 (0.07)** | −0.08 (0.08) | 0.03 (0.08) |
| Network Size | −0.01 (0.07) | −0.31 (0.07)** | 0.08 (0.09) | −0.41 (0.08)** |
| Duration | −0.03 (0.07) | 0.03 (0.07) | 0.17 (0.08)* | 0.16 (0.08)* |
| Media use[a] | 0.43 (0.07)** | 0.18 (0.07)** | 0.38 (0.09)** | 0.29 (0.08)** |
| Network Size × Media use | 0.02 (0.09) | | −0.04 (0.10) | |
| Duration of use × Media use | 0.03 (0.07) | | 0.07 (0.09) | |
| Gender × Media use | −0.08 (0.06) | | −0.03 (0.08) | |
| Age × Media use | 0.14 (0.07)* | | 0.04 (0.11) | |
| Network Size × Duration of use | −0.21 (0.08)* | | −0.10 (0.10) | |
| Gender × Network Size | 0.21 (0.07)** | | −0.05 (0.10) | |
| Age × Network Size | −0.07 (0.07) | | 0.30** (0.09) | |
| Gender × Duration of use | −0.12 (0.06) | | −0.11 (0.09) | |
| Age × Duration of use | 0.01 (0.07) | | −0.08 (0.09) | |
| Gender × Age | 0.09 (0.07) | | 0.04 (0.08) | |
| Observations | 212 | 144 | 212 | 144 |
| Adjusted $R^2$ | 0.23 | 0.21 | 0.14 | 0.19 |
| F Statistic (df) | 5.22** (15; 196) | 3.53** (15; 128) | 7.78** (5; 206) | 7.67** (5; 138) |

Note. General ambient awareness is awareness towards the network in general; Awareness of targets is the average awareness of individual targets (maximum 17 per participant in Study 1 and 20 per participant in Study 2).
* $p < 0.05$; ** $p < 0.01$.
[a] General social media use in Study 1 and Twitter use in Study 2.

## 4. Study 2

### 4.1. Methods

#### 4.1.1. Procedure

The procedure was identical to Study 1, except for how we presented individual profiles at the second stage of the questionnaire. Each participant saw 20 profiles for which they had to indicate whether they recognize them. From the recognized profiles, three were randomly selected and participants received additional questions, similar to those in Study 1.

#### 4.1.2. Participants

Recruitment and reimbursement were the same as in Study 1. Of the 212 respondents, 64 were excluded: 63 for failing the attention checks and one for having an account in Twitter for less than half a week prior to the study. The final sample consisted of 148 participants (68% female), 36% employed, 30% homemaker, 20% self-employed or looking for work, unable to work, student, or retired (11%, 6%, and 7%, respectively). The mean age was 41 years ($SD = 12$). After excluding one outlier, the mean network size was 519 ($SD = 634$; $Mdn = 217$) with 4 years ($SD = 2$) average duration of Twitter use.

#### 4.1.3. Materials

**Ambient awareness**. General ambient awareness and number of people for whom it is experienced were measured with the same questions used in Study 1. For awareness of individual targets, we used 8 items (see Table 2). The items were rated on a continuous scale, using a slider with anchor points 1 = not at all and 7 = extremely. The internal consistency was moderately high (Chronbach's alpha = 0.84) and the scale was treated as unidimensional.

**Network**, **media use**, **and demographics**. We changed the assessment of Twitter use in Study 2 to hours per week spent on the site to avoid the ceiling effect from Study 1. Age, which was a categorical variable in Study 1, was measured in years. All other variables remained unchanged.

**Table 2**
Target awareness: ambient awareness of individual online-only contacts.

| Items | *M* | *SD* |
|---|---|---|
| **Target Awareness Scale** (**Chronbach's Alpha** = **0.84**) | | |
| I feel like I know what {Name} is like as a person. | 4.37 | 1.58 |
| {Name}'s tweets allow me to get to know him/her at least somewhat. | 4.72 | 1.34 |
| {Name} is a complete stranger to me.[a] | 3.61 | 1.76 |
| {Name}'s is a person, I would be able to find a topic to talk about. | 5.16 | 1.33 |
| I have no idea what {Name} would be like in real life.[a] | 3.88 | 1.68 |
| I know what {Name} might be knowledgeable about. | 5.06 | 1.42 |
| I am aware of {Name}'s profession or professional interests. | 5.14 | 1.59 |
| I have an idea of what {Name}'s hobbies are. | 4.24 | 1.69 |

Note. {Name} was substituted with the name and username of individual Twitter contacts.
[a] Reverse-coded items.

**Communication and relationship duration**. Passive communication was measured by asking participants how frequently they read tweets from the given person, from 1 (never) to 7 (all the time). Active communication was measured with two items, one asking how frequently the participants interacted with the target and one asking how frequently the target interacted with the participant, answered on scales from 1 (never) to 7 (all the time). We additionally assessed relationship duration by asking participants for how long they have been following a given target on a scale from 1 (less than a week) to 5 (more than a year).

### 4.2. Results

#### 4.2.1. Ambient awareness

The average general awareness reported in Study 2 was 6.32 ($SD = 2.25$). The majority of people reported experiencing ambient awareness for between few and more than several people (75%), but less than half of the network. These patterns were similar to what we observed in Study 1.

Due to the revised survey procedure in Study 2, we were able to calculate the likelihood of recognizing individual contacts. The mean likelihood was 64% ($SD = 38$), which again is fairly high

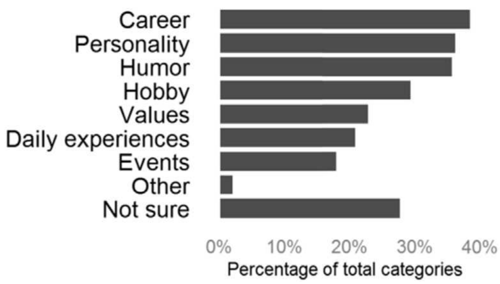


**Fig. 2.** Distribution of information categories in Study 2.

considering the large networks of the participants.

*4.2.2. Ambient awareness of individual targets*

As in Study 1, we excluded targets with close relationship to the participants (i.e., family, close friends, and friends; 2%). In Study 2, we included an additional 8-item measure to assess ambient awareness of individual targets (Table 2). The average ambient awareness of targets known only through Twitter was moderately high ($M = 4.51$, $SD = 1.05$).

*4.2.3. Information about individual targets*

Frequencies of reported information categories can be seen in Fig. 2. The most common categories were similar to those in Study 1. It should also be noted that in both studies, the category *not sure* was chosen frequently, which is in line with the idea that ambient awareness can be vague as well as specific.

*4.2.4. Demographic, network, and media use variables (RQ2)*

The analysis strategy was the same as in Study 1. Model summaries can be seen in Table 1b. Consistent with what we found in Study 1, frequency of Twitter use was positively associated with both indexes of awareness. Network size was negatively correlated with awareness of individual contacts but not with the general experience of awareness. There was a small effect of duration of use and an interaction between age and network size. However, these effects were not consistent across studies, indicating that they are likely not robust or even spurious. We do not interpret these effects and conclude that network size and frequency of use were the only factors with consistent effects across the two studies.

The effects of relationship duration and types of communication were investigated on the level of individual targets. Due to the nested nature of the data (multiple targets per participant), multilevel models were conducted with random intercepts for participant and all factors of interest as fixed effects. Ambient awareness of the target was regressed on passive communication, active communication with target, active communication with participant, and relationship duration. All variables were standardized. As can be seen in Table 3, only the frequency with which participants read the target's posts (passive communication) and interacted with the target (active communication with target) emerged as significant predictors. Our data support the claim that ambient awareness arises on the basis of frequent exposure to bits and pieces of information (passive communication). Relationship duration had no significant effect on ambient awareness, suggesting that awareness is not strictly dependent on extended period of interaction.

**Table 3**
Model summary of multi-level model of the effects of communication and relationship duration on awareness of individuals.

| | Target awareness |
|---|---|
| Passive communication | 0.36 (0.06)** |
| Relationship duration | 0.07 (0.05) |
| Active comm with T | 0.21 (0.09)* |
| Active comm with P | −0.03 (0.08) |
| Observations | 352 |
| Log Likelihood | −432.30 |

Note: Target awareness is ambient awareness of individual target (average of 8-item scale).
Active comm with T = participant interacts with target.
Active comm with P = target interacts with participant.
* $p < 0.05$; ** $p < 0.01$.

*4.2.5. Perceptions of approachability (RQ3a)*

The frequency of reading a target's posts was positively associated with perceptions of approachability ($\beta = 0.32$, $SE = 0.05$, $p < 0.01$). Our data indicate that ambient awareness mediated the relationship. The frequency of reading posts was positively related to ambient awareness ($\beta = 0.48$, $SE = 0.05$, $p < 0.01$) and ambient awareness was positively related to perceptions of approachability ($\beta = 0.53$, $SE = 0.05$, $p < 0.01$). To test for mediation, we regressed perceptions of approachability on both frequency of reading posts and ambient awareness. As can be seen in Fig. 3, the relationship between ambient awareness and approachability remained significant while controlling for reading posts, whereas the relationship between reading posts and perceptions of approachability was reduced, as compared to the direct relationship. Although our design was correlational the pattern suggests mediation and offers support for the idea that browsing social media results in ambient awareness, which has a positive impact of perceptions of approachability.

*4.2.6. Expertise awareness (RQ3b)*

As in Study 1, expertise awareness was assessed by asking participants whether they can indicate the areas of the target person's hobbies and profession. They were also able to select *not sure* and *no idea* if that were the case. Again, having some knowledge of hobbies and profession was common. Knowledge of targets' hobbies, profession, or both was reported for 85% of the targets. Information of hobbies and profession reveal what a person is knowledgeable about and can help social media users identify who knows what in their network and thus locate potential sources of information.

## 5. General discussion

The aim of this research was to explore the idea that the passive browsing of social media timelines, increases the awareness that users have of their online networks (ambient awareness). It has been speculated but not previously demonstrated that reading updates on social media can result in ambient awareness, that is, familiarity with people within an online network. We conducted two surveys and found that people experienced moderately high levels of ambient awareness towards their network on the microblogging site Twitter and were able to report specific knowledge of people they follow on Twitter but had not met in real life.

Our research provides evidence for a central aspect of ambient awareness, which has not been explicitly addressed in prior research. Namely, that awareness in social networks can develop peripherally, from fragmented information and in the relative absence of extensive one-to-one communication. Focusing on Twitter allowed us to demonstrate that microblogging updates are sufficient for ambient awareness to develop.

Prior qualitative work has shown that people report ambient awareness (e.g., Zhao & Rosson, 2009), but it was not clear whether they become only aware of some very active network members or

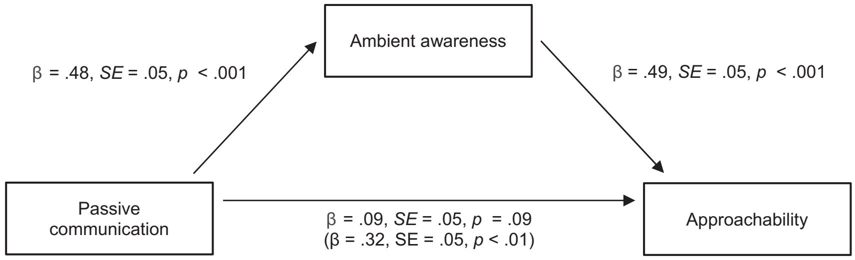


**Fig. 3.** The mediating role of ambient awareness on perceptions of approachability.

develop a feeling for a large proportion of their network. Most participants estimated having ambient awareness for more than several people but less than half members of their network. This suggests that although ambient awareness is not present for each online contact, it is also not limited to a small number of very active network members.

We took the assessment of ambient awareness a step further by developing a Twitter network survey procedure through which we selected individual people our participants followed on Twitter. Even though the majority of participants followed hundreds of people, they were able recognize individual members of their online-only contacts and report specific information about them.

Contrary to the idea that ambient awareness develops over extended periods of time, neither duration of Twitter use nor relationship duration predicted awareness. The general experience of ambient awareness was not influenced by network size, showing that people with large online networks can still experience a sense of knowing their social media contacts. However, they were less likely to recognize and report awareness of individual contacts, presented during the survey.

The frequency of media use was positively associated with ambient awareness. Frequency of use can be seen as indicator of experience, in which case the relationship is consistent with one of the predictions of electronic propinquity theory, namely that communicators who have experience with a given medium would benefit more from its use. Frequent use also supposes higher exposure to content, which allows for a sense of awareness to build up from fragmented information. The importance of frequent exposure is also seen on an individual level, where the ambient awareness of specific target was predicted by how often the participant received updates from the target (passive communication).

Most commonly reported was knowledge of personality, humor, hobbies, and career. The prevalence of personality and humor awareness is in line with the well-documented spontaneity of trait inferences (Uleman et al., 2008). Information about hobbies and career reveals what people are interested in and knowledgeable about. Apart from serving as topic for conversation, this information can allow social media users to gain awareness of who knows what in their network (Leonardi, 2015).

### 5.1. Limitations and future research

The present research is descriptive and largely exploratory. Although we provide converging data from two studies, additional research is needed to validate and further understand the effects we observed. We identified potential antecedents and moderators of ambient awareness, but the data were correlational. Future research can adopt methods that allow for a closer inspection of underlying processes.

The research relied on self-reported information regarding participants' own networks. While the method contributed to the ecological validity of the research, it posed restrictions to extent to which the accuracy of responses can be determined. One question is whether the participants' responses indeed reflected their actual impressions of the targets, as opposed to being formed on the spot, when participants were asked to report them. Future studies could use constructed materials and multiple judgments to definitively resolve these issues.

### 5.2. Implications

Online networks are unprecedented in size and structure. Their vastness and diversity create a potential for gaining enormous relational and information benefits (Donath, 2007), but pose a serious challenge to traditional relational maintenance strategies (Tong & Walther, 2011). As with other forms of ambient contact (e.g., Ito, 2005; Romero et al., 2007), ambient awareness is envisioned as a cognitively efficient process contributing to relational communication. Many have discussed the potentially negative effects of frequent media use when it serves as recurring distraction or leads to information overload. Seeing ambient awareness as cognitively efficient is not necessarily at odds with these findings. Rather, the efficiency stems from ambient awareness developing without cost or effort beyond what is already invested in browsing, which does not imply that browsing social media is in itself an efficient process.

One way in which awareness relates to social processes is through providing people with information about others. Such information can serve as a basis of first impressions and result in a sense of familiarity, both of which can make a target appear more approachable. This idea is supported by our data. In addition to perceptions of familiarity and approachability, ambient awareness can make it easier to approach others by providing topics for conversation. For example, somebody's social media activity can reveal that the person is an avid Joy Division fan or has recently visited a tropical island, both of which can easily serve as conversation starters. On an even more practical side, picking up on cues that somebody is stressing over an upcoming deadline is a good indication that this person might not be able or willing to respond promptly if approached.

The relational effects of ambient awareness can be linked to informational processes, because the relationship between an information seeker and source is essential to information exchange. A recent study demonstrated that connecting to a person on social media facilitated subsequent information transfer from this person (Leonardi & Meyer, 2014). The authors turn to ambient awareness to explain the link between browsing and facilitated social interaction, but do not specifically assess ambient awareness. By demonstrating that ambient awareness mediated the relationship between the frequency of reading microblogging updates and perceptions of approachability, we complement their findings and offer further support for the proposed process.

As discussed earlier, online network provide abundant valuable information, but finding efficient ways to navigate them and successfully locate information is a challenge. We found that ambient awareness involves information about hobbies and profession. Such information can enable social media users to develop a cognitive map of who knows what in their online network. Awareness of who knows what offers a potential solution to the problem of locating valuable information without needing to post public or widely shared requests. The role of expertise or knowledge awareness (who knows what) in information processes has been discussed widely in the context of collaborative work and knowledge exchange in organizations (e.g., Engelmann, Dehler, Bodemer, & Buder, 2009), but not with regard to public social media. The potential of bridging these lines of inquiry is substantial, as networks on public social media are virtually unlimited and far more diverse than organizational or other professional networks.

## 6. Conclusion

Computers and mobile devices are with us at every step of our daily lives (Vorderer, 2015). Social media and networking sites broadcast bits of information about every member of our increasingly large and diverse online networks. Often meaningless in isolation, these bits can easily be seen as random noise and clutter. Without questioning the potentially problematic effects of being permanently connected, we focused on how this incessant contact enhances our digital lives. This research is a first step towards understanding the intriguing construct of ambient awareness. We demonstrate that browsing social media and frequently encountering various social information allows social media users to gain awareness of what is going on in the lives of people in their online network. The efficacy, scope, and functionality of ambient awareness are yet to be established. We provide evidence that browsing microblogging updates is sufficient for awareness to develop and highlight ways in which it can help bring about relational and informational benefits of online networks.

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# Appendix B

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# Spontaneous Trait Inferences on Social Media

**Ana Levordashka[1] and Sonja Utz[1]**


## Abstract

The present research investigates whether spontaneous trait inferences occur under conditions characteristic of social media and networking sites: nonextreme, ostensibly self-generated content, simultaneous presentation of multiple cues, and self-paced browsing. We used an established measure of trait inferences (false recognition paradigm) and a direct assessment of impressions. Without being asked to do so, participants spontaneously formed impressions of people whose status updates they saw. Our results suggest that trait inferences occurred from nonextreme self-generated content, which is commonly found in social media updates (Experiment 1) and when nine status updates from different people were presented in parallel (Experiment 2). Although inferences did occur during free browsing, the results suggest that participants did not necessarily associate the traits with the corresponding status update authors (Experiment 3). Overall, the findings suggest that spontaneous trait inferences occur on social media. We discuss implications for online communication and research on spontaneous trait inferences.



## Keywords

spontaneous trait inferences, false recognition, social media, Internet/cyberpsychology, impression formation, person perception


Social media allow people to communicate at virtually no cost and effort and build large online networks, which can be powerful sources of social and emotional support (Donath, 2007). The challenge lies in finding successful ways to maintain and navigate those networks, since their size and diversity render traditional maintenance strategies, such as face-to-face communication, less feasible (Resnick, 2001; Tong & Walther, 2011). Snap social processes like spontaneous inferences present a potential solution. Research has shown that people spontaneously infer traits, goals, and values from minimal exposure to information (Uleman, Saribay, & Gonzalez, 2008). Social media offer a near constant stream of information, and if inferences indeed require no more than a passing glance, browsing might help users gain awareness of their online networks (Levordashka & Utz, 2016; Thompson, 2008). However, the extent to which such snap inferences are made online is not clear. We examine key conditions that could hinder spontaneous inferences on social media and report experiments designed to test whether inferences occur under these conditions.

In research on online impression formation, it is common to explicitly ask participants to judge others, whose profiles they view at their own pace (e.g., Antheunis & Schouten, 2011; Back et al., 2010; Evans, Gosling, & Carroll, 2008; Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011; Pennington & Hall, 2014; Westerman, Van Der Heide, Klein, & Walther, 2008). In contrast to this deliberate evaluation, browsing involves skimming through information without any particular intention. Even if the encountered posts contain relevant cues, we do not know whether these cues will lead to inferences when people encounter them briefly and without explicit impression formation goals.

There is robust evidence that people spontaneously infer social information and form impressions (Ambady & Rosenthal, 1992; Uleman et al., 2008), which can persist over time and affect behavior (Todorov, Mandisodza, Goren, & Hall, 2005; Todorov & Uleman, 2004). Here, we focus on behavioral descriptions as a cue (Carlston, Skowronski, & Sparks, 1995; Uleman et al., 2008). Studies have shown that when reading about others' behavior, people make inferences even when their task is unrelated to impression formation or when they are under high cognitive load (Todorov & Uleman, 2003). Status updates often contain trait-implying information and can therefore be expected to produce similar effects. However, the evidence for spontaneous trait inferences comes from laboratory experiments with conditions that differ from social media in important ways.

Spontaneous trait inference experiments typically use third-party descriptions (Rim, Uleman, & Trope, 2009; Saribay,

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Rim, & Uleman, 2012; Todd, Molden, Ham, & Vonk, 2011), which are particularly powerful in driving impressions. Even when first-person descriptions are used (e.g., Carlston et al., 1995), the information is provided to the participants with no context, and there is little reason to doubt its accuracy. Social media updates, however, are self-generated and shared voluntarily, which makes them less reliable due to strategic self-presentation (warranting principle; Utz, 2010; Walther, Van Der Heide, Kim, Westerman, & Tong, 2008).

Moreover, the information in laboratory experiments can be of rather extreme nature. Behaviors such as "She threw a chair at her classmate" (Bliss-Moreau, Barrett, & Wright, 2008) or "I kicked [a puppy] out of my way" (Carlston & Skowronski, 1994; Carlston et al., 1995; McCarthy & Skowronski, 2011) are used as stimuli, but would rarely be shared online, where information tends to be more mild and appropriate (Utz, 2014). This is problematic because extreme information is known to influence impressions more strongly (Fiske, 1980; Skowronski & Carlston, 1989). Indeed, researchers have speculated that too mild content might not result in spontaneous inferences (Skowronski, Carlston, & Hartnett, 2008).

Another major difference lies in how information is presented. Nearly, all experiments on spontaneous trait inferences present only one pair of actor and behavior at a time. Forming a distinct association under such conditions is more straightforward than on social media, where different actors and behaviors appear in parallel and users browse through without being particularly attentive. A social media user could easily be looking at one person, while still processing information about another, especially while browsing.

Since updates on social media are self-generated and often mild in content, it is not clear whether they will be sufficiently powerful as a cue to produce spontaneous inferences. Furthermore, viewing multiple updates in parallel and in "browse" mode might hinder the associative process. In a series of experiments, we tested whether people will spontaneously infer traits from mild, self-generated social media updates (Experiment 1), when information is presented in parallel (Experiment 2) and merely browsed through (Experiment 3).

## General Method

### Overview

We adapted an established trait-inference paradigm (false recognition; Todorov & Uleman, 2002). The paradigm assesses trait inferences via a recognition task. First, participants see a number of actors paired with brief trait-implying descriptions. They are asked to read the descriptions without any mention of impression formation (learning phase). In a subsequent recognition task, the same actors are paired with single words, and for each pair, participants indicate whether the word appeared in the actor's description. It has been shown that if the target word is the trait implied by the actor's description, participants make more mistakes saying that it was in the description (Todorov & Uleman, 2002). This false recognition of implied traits occurs because, while reading the descriptions, participants spontaneously infer the implied traits and associate them with the corresponding authors. When developing the paradigm, researchers adopted additional control conditions and counterbalancing to rule out alternative explanations, such as mere word activation, and effects of extraneous characteristics of the stimuli. It was consistently demonstrated that the counterbalancing had no effect, which led the authors and other researchers employing the paradigm to drop the counterbalancing.

We followed the same procedure but changed the content and presentation of stimuli. The stimuli were social media updates, ostensibly posted by the actor (self-generated) and nonextreme (appropriate) in content. Experiment 1 followed the original paradigm but with status updates as stimuli. In Experiment 2, we used the same content and varied the number of updates presented simultaneously. In Experiment 3, participants browsed through all updates at their own pace. Our primary dependent variable was the number of mistakes (false recognitions). Whether trait inferences will be made in these conditions is an open question. What we hypothesize and test in each experiment is that if trait inferences occur, participants will make more mistakes for implied traits as compared to other traits.

Prior research has assessed response times (RTs) to correct trials. Since longer RTs can be indicative of greater difficulty, it can be expected that if spontaneous inferences are made, RTs to implied traits should be longer. Although there has been some supporting evidence, RTs are not a reliable indicator of trait inferences. Nevertheless, to be consistent with prior work, we recorded and reported RTs. In addition to false recognitions, we developed an alternative assessment of impressions.

We report how we determined sample size, all data exclusions, manipulations, and measures (Simmons, Nelson, & Simonsohn, 2012). The design and hypotheses were preregistered (osf.io/jqhdz). The experiments were designed in PsychoPy (Peirce, 2007) and analyzed in *R* (R Core Team, 2015). The research was approved by an ethics committee.

We conducted pilot research for Experiments 1 and 2, which is not reported here, but a report is available online (Levordashka, 2016). The results are consistent with the remaining experiments and including them in the article would not have altered our conclusions.

### Sample

The effect sizes in spontaneous trait inferences experiments using the false recognition paradigm are moderately large (Todorov & Uleman, 2002). A sample of 16 participants would have been sufficient to achieve statistical power of 0.95 in a two-tailed dependent-samples *t*-test. We have decided on larger samples to ensure power of at least 0.90 for effect sizes of $d_z = 0.60$.

For all experiments, participants were recruited from the participant pool of a German research institute. Some experience with social media was called for during recruitment but not subsequently assessed. Since prior research has not found


**Figure 1.** Example of status update stimulus. The actual stimulus had a different face and name, and the text was in German.

gender differences in spontaneous impression formation, we did not consider it necessary to discriminate participants based on their gender to ensure a balanced sample. Gender distribution is reported per experiment. Other demographic information was collected separately and reported for the sample across experiments. The participants were undergraduate students of various faculties (no discipline was represented by more than 10%). Age ranged from 19 to 34 years ($M = 24$, $SD = 3$).

# Experiment 1

## Method

### Participants

Thirty participants took part in the study (22 female). After providing an informed consent, participants received instructions and completed the study on individual computer screens. The total duration was 15 min. At the end, participants were debriefed and reimbursed (2 EUR).

### Procedure

Participants saw 36 social media updates (Figure 1), which they were asked to read carefully (learning phase). On each trial, a single update was presented for 5 s. In the recognition task, participants saw each face from the learning phase, paired with a word, and had to indicate as quickly as possible whether the word had appeared in the status update of the person (*old* word) or whether it is a *new* word that was not in the update. For example, if person A's description was "Just spilled coffee all over my laptop!" and in the test phase person A appeared with the word *laptop*, the correct response would be *old*; any word that was not in the update (e.g., *clumsy*) would be a *new* word. The presentation order of single trials was randomized in each task and for each participant.

For the updates, we used 36 sentences (in German), 12 of which mentioned a personality trait and 24 implied a trait without explicitly mentioning it. The associations between sentences and implied traits were pretested. The number of positive and negative sentences was balanced.

The sentences were randomly paired with 36 faces from Bainbridge, Isola, and Oliva (2013). We used equal number of male and female faces of similar attractiveness and memorability (based on the ratings from the database).

For the recognition task, each face was paired with a word. Everyone faces whose status update mentioned a trait were paired with this same trait (presented trait). The remaining 24 sentences were split into three groups: eight faces were paired with the trait implied by the status update of the same actor (implied-trait condition); eight faces with the trait that was implied by a status update of another actor (other-trait condition); eight faces with a novel trait (control-trait condition). Presented-trait trials served as fillers and were not analyzed. The correct response to all other trials was *new*. Responses *old* were coded as errors (false recognitions).

### Memory of Stimuli

We assessed participants' memory for the sentences form the learning phase in a recall task. Participants saw a random selection of six faces and had to type the corresponding updates. The responses were coded by research assistants unaware of the study design. The scale for accuracy was: 0 = *no response*, 1 = *not at all accurate*, 2 = *accurate meaning; mistakes in wording*, 3 = *mostly accurate*, 4 = *accurate*. Another item assessed whether participants recalled a sentence but paired it with the wrong target. If a participant's response was a somewhat accurate recollection of one of the stimulus sentences but not that of the target face, the response was coded as mistaken target. Intercoder reliability was estimated on 20% of the responses, with ratings from two coders (intraclass correlation coefficient [ICC] = .93, 95% confidence interval [CI] [0.83, 0.97]).

### Direct Assessment of Impressions

Participants were asked to evaluate some of the actors ($n = 12$ per participant) from the learning phase. On each trial, they saw a face, paired with two traits: The trait implied by the status update and another trait of the same valence and had to choose one of the traits to evaluate the person. This assessment of impressions was an additional measure of trait inferences.

### Excluded Cases

Our a priori criterion was 3 *SD* above or below the sample mean for each measure in the study. There were no outliers. One participant made no correct responses in the implied-trait condition. Since the RT analyses were based on correct trials, this resulted in missing data. To ensure a balanced design, we excluded this participant from the RT analysis. Alternative approaches (replacing the missing data with the participant's average RTs in the other conditions or with the average RTs of other participants in the missing condition) yielded similar results.

## Results

We used paired-sample *t*-tests to test our hypothesis regarding false recognition rates (Table 1). Participants made more mistakes when an actor's face was paired with the trait implied for this actor (implied-trait condition; $M = 0.55$, $SD = 0.24$) as compared to a trait implied for another actor (other-trait condition; $M = 0.34$, $SD = 0.22$) or a novel trait (control condition; $M = 0.23$, $SD = 0.17$). This pattern suggests that people

**Table 1.** Results of Dependent-Samples *t*-Tests Comparing False Recognition Rates across Conditions (Experiment 1).

| Comparison | *df* | *t* | Sig. (Two Tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| Implied–other | 28 | 4.15 | <.001 | 0.89 [0.41, 1.4] |
| Implied–control | 28 | 6.21 | <.001 | 1.47 [0.89, 2.13] |
| Other–control | 28 | 2.93 | .007 | 0.52 [0.15, 0.91] |

*Note.* CI = confidence interval.

spontaneously inferred traits when reading status updates with mild content, written from a first-person perspective.

Average RTs to correct trials ranged between 1.03 and 3.24 s ($M = 2.15$, $Mdn = 2.22$, $SD = 0.54$). The data violated assumptions of normality. We performed a log10 transformation on the row data (RTs per trial). To avoid negative values, we added 1.0 to all values prior to the transformation. Following the transformation, the data no longer violated assumptions of normality and equal variances (Shapiro Wilk's $p$s > .06; Levene's test $p$s > .1). There were no significant differences in RTs (all $p$s > .087).

The recall of the stimulus material was low. For 40% of the trials, participants were not able to recall anything and 42% of the recalled sentences were classified as "*not at all accurate.*" As we expected, participants occasionally recalled the status update of a person other than the one whose picture was displayed. This however occurred in only 16% of the cases, which indicates that overall retention of the stimuli was indeed low.

The occurrence of spontaneous inferences was apparent in the direct evaluations measure. When asked to evaluate the actors from the learning task, participants selected the implied trait over another trait of the same valence 62% of the time. An exact binomial sign test indicated that this was significantly higher than chance, 95% CI [0.55, 0.69], $p = .001$. Given the low recall, this preference is likely due to implicit evaluation based on the actor's update rather than direct recall of the update.

## Discussion

The results of this experiment show that the content typically encountered on social media can result in spontaneous trait inferences. These inferences were reflected in the outcome of a word recognition task: Participants were more likely to falsely recognize a word as having been previously mentioned in an actor's status update, when the word was the trait implied by the update, as compared to traits implied for other actors and to novel traits.

We also found that when directly asked to evaluate a person, participants were more likely to choose the trait, implied by this person's update. Importantly, this likelihood was higher than what the memory of stimulus materials would suggest. That is, participants' evaluations were driven by status updates they had previously seen but could likely no longer recall.

In sum, we provide evidence for trait inferences on the basis of ostensibly self-generated status updates. However, the possibility remains that if too much information is presented at once, there will not be clear associations and person-specific inferences. The following experiment was designed to address this concern.

# Experiment 2

## Method

Nineteen participants took part in the experiment (16 female). The recruitment, procedure, stimuli, and measures were identical to that in Experiment 1, with the exception of how we presented the stimuli. Instead of one at a time, participants saw nine updates in each of the four trials (60 s per trial). In the test phase, the implied-trait condition remained unchanged. There were two comparison conditions: Faces paired with traits implied by other updates from the same trial and faces paired with traits from other trials.

There were no outliers based on the three *SD* criterion. One participant had to be excluded from the analysis of RTs because they made no correct responses in the implied-trait condition, which resulted in missing data.

## Results

The number of false recognitions differed significantly across conditions (Table 2). Participants made considerably more mistakes when an actor's face was paired with the trait implied for this actor (implied-trait condition; $M = 0.57$, $SD = 0.23$), as compared to a trait implied for another actor in the same trial ($M = 0.3$, $SD = 0.15$) or another trial ($M = 0.29$, $SD = 0.18$). There was no significant difference between the two control conditions. Crucial here is the difference in false recognitions between traits implied by status updates that were presented during the same trial. Although the updates appeared simultaneously, the trait implied by each update was specifically associated with the person who posted the update.

RTs to correct trials ranged between 1.1 and 5.59 s ($M = 2.46$, $Mdn = 2.41$, $SD = 0.99$). Due to violated assumptions of normality, we performed a log10 transformation on RTs per trial (1.0 was added to all values). Following log transformation, the data no longer violated the assumptions of normality and equal variances (Shapiro Wilk's $p$s > .09; Levene's test $p$s > .79). RTs for correct responses for implied-trait trials ($M = 3.11$, $SD = 0.92$) were shorter than in the other two conditions (same trial: $M = 3.49$, $SD = 0.97$; other trial: $M = 3.46$, $SD = 1.01$; Table 3).

The recall of status updates was low. On the majority of trials, participants provided no response (47%) or a highly inaccurate response (28%). There were some cases of recalled update but a mistaken target (18%), which shows that participants recalled more than their raw memory scores suggest. Even when considering these cases, the overall recall was low.

Despite having poor recall of the seen updates, when asked to evaluate an actor, participants chose the implied trait over another trait of the same valence 75% of the time, which was significantly higher than chance, 95% CI [0.66, 0.82], $p < .0001$. These results provide evidence that participants made actor-specific trait inferences.

**Table 2.** Results of Dependent-Samples *t*-Tests Comparing False Recognition Rates Across Conditions (Experiment 2).

| Comparison | *df* | *t* | Sig. (Two Tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| Implied–other (st) | 18 | 6.17 | <.001 | 1.32 [0.75, 2] |
| Implied–other (ot) | 18 | 5.14 | <.001 | 1.3 [0.67, 2.03] |
| Other (st)–other (ot) | 18 | 0.35 | .734 | 0.08 [−0.38, 0.54] |

*Note.* st = same trial; ot = other trial; CI = confidence interval.

**Table 3.** Results of Dependent-Samples *t*-Tests Comparing RTs across Conditions (Experiment 2).

| Comparison | *df* | *t* | Sig. (Two Tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| Implied–other (st) | 17 | −4.91 | <.001 | −.42 [−.67, −.21] |
| Implied–other (ot) | 17 | −2.92 | .010 | −.39 [−.72, −.1] |
| Other(st)–other (ot) | 17 | 0.25 | .805 | .03 [−.22, .28] |

*Note.* st = same trial; ot = other trial; CI = confidence interval.

## Discussion

Experiment 2 provided evidence that the simultaneous presentation of status updates can result in distinct, actor-specific inferences. Participants were more likely to falsely recognize an implied trait as having been previously presented, which indicated that they spontaneously inferred the trait. They were also more likely to associate an actor with the trait implied by this actor's update, without necessarily being able to recall the update. We did not find the expected differences in RTs.

Unique to this experiment is the demonstration that when participants viewed updates simultaneously, the traits they inferred from each update were distinctly associated with the author of the update and not with the other actors whose picture and update they viewed at the same time. However, the experimental setup does not rule out the possibility that browsing poses a boundary condition to this association. We therefore conducted a third experiment, in which participants browsed through the updates at their own pace in a setup that closely resembled social media.

## Experiment 3

## Method

Forty-five participants took part in the study (37 female). Recruitment was identical to that in previous experiments and we used a similar procedure. The stimulus material was the same as in the previous experiments, but instead of presenting the status updates in discrete trials for fixed amount of time, all updates appeared on a time line and participants could scroll through for as long as they like. They were instructed to mark the updates they found interesting and proceed when ready (browsing time was recorded). In the test phase, the experimental conditions were the same as in Experiment 1: implied trait, other trait, and a novel trait.

### Scenario-Based Evaluation Measure

We developed a novel scenario-based measure of direct impressions. On each of four trials, participants read a situation and were asked to make a choice between two people. The situations were such that a person with certain trait would be preferred (e.g., "Who would you rather give your house key to?" would likely be somebody who is trustworthy rather than unreliable). For each question, participants had a choice between two actors: one for which the desired trait was implied and one for which an opposite trait was implied. We compared the likelihood of choosing a person with a desired trait over a person with an undesired trait. To control for the influence of faces, for every pair of actors in a scenario, we swapped the traits implied during the learning phase. This manipulation was done between participants. That is, already in the learning phase, for half of the participants, person A was paired with the desired trait and, for the other half, person A was paired with the undesired trait.

### Excluded Cases

There were no outliers in the false recognitions measure and one RT outlier, who was excluded from the RT analysis. We excluded one more participant from the RT analysis due to missing data: They had no correct responses in the implied-trait condition.

## Results

On average, participants spent 2.42 ($SD = 1.19$) min browsing the updates, which is an average of 4 s per update. They marked 20% ($SD = 15$) of the updates as interesting. Browsing time was positively correlated with memory of the stimulus updates ($r = .32$, $p = .032$) but not with error rates ($r = .18$, $p = .243$). The number of interesting updates was positively correlated with browsing time ($r = .51$, $p < .001$). All zero-order correlations are reported in the supplemental material.

The pattern of means was consistent with our previous findings: higher number of error rates in the implied-trait condition ($M = 0.43$, $SD = 0.25$) as compared to other-trait ($M = 0.37$, $SD = 0.21$) and control ($M = 0.24$, $SD = 0.19$). The difference between implied and other-traits was small and only approaching significance (Table 4). Given that the means are in line with our hypothesis and a one-sided test (justified by our preregistered directional prediction) would have been significant, we consider that spontaneous inferences did occur. There was also a significant difference between the other- and control-trait condition, which we did not find in the previous experiments. If we are to interpret this pattern according to Todorov and Uleman (2002), we would conclude that inferences occurred (the least mistakes were made for novel traits) but were not successfully bound to corresponding faces (no difference between correctly paired trait-face trials, i.e.,

**Table 4.** Results of Dependent-Samples *t*-Tests Comparing False Recognition Rates across Conditions (Experiment 3).

| Difference | *df* | *t* | Sig. (Two Tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| Same–other | 45 | 1.94 | .058 | 0.28 [−0.01, 0.57] |
| Same–control | 45 | 5.33 | <.001 | 0.86 [0.5, 1.24] |
| Other–control | 45 | 4 | <.001 | 0.62 [0.29, 0.96] |

implied trait condition, and mismatched pairs, that is other-trait condition).

RTs to correct trials ranged between 0.84 and 3.78 s ($M$ = 2.04, $Mdn$ = 1.96, $SD$ = 0.69). Following a log10 transformation (per trial; 1.0 added to each value), the data no longer violated the assumptions of normality and equal variances (Shapiro Wilk's $ps > .02$; Levene's test $ps > .11$). Only the difference between implied and novel traits was significant, $t(43) = 2$, $p = .052$ (all other $ps > .146$).

The recall of status updates was low. Responses were mostly absent (45%) or highly inaccurate (41%). Occasionally, participants recalled the sentence of a different actor from the data set (17%).

The results of our scenario-based assessment offer support for the occurrence of trait inferences. Across four different scenarios, participants selected the actor whose status update implied a trait that would be desirable in the particular scenario 61% of the times, which was significantly higher than chance, 95% CI [0.54, 0.68], $p = .002$.

## Discussion

Evidence for spontaneous inference during browsing was found in the direct evaluation measure. In the false recognition measure, the difference between the implied- and other-trait conditions was not significant. According to the traditional interpretation of the paradigm, this pattern suggests that inferences occurred (the least mistakes were made for novel traits) but were not successfully bound to corresponding faces, as indicated by the small difference between correctly paired trait-face trials (implied-trait condition) and mismatched pairs (other-trait condition). However, it is not clear whether this pattern is robust. The pattern of means corresponds to what was found in the first two experiments and we found evidence for inferences in the alternative measure, which renders the possibility that the effect was present but weaker.

## General Discussion

The information social media users encounter online is rich in social cues. Psychological research on first impressions suggests that even without attending to the social aspects of information, users might form impressions based on that information. Despite this possibility and its implications, spontaneous inferences have not been studied in the context of social media. We provide evidence that trait inferences occur spontaneously from content and under conditions resembling social media (Figure 2).

Participants spontaneously formed impressions on the basis of single, nonextreme, ostensibly self-generated status updates without being instructed to do so. Our research supports the robustness of spontaneous trait inferences and their relevance for online communication.

Prior research has shown that person inferences are unintentional, cognitively efficient, long-lasting, and can be of traits but also values, goals, or intentions (Uleman et al., 2008). This makes them highly relevant for online communication, where information is often merely glanced at. Our work is an important first step toward examining the impact of spontaneous impression formation on relational and informational processes online.

We used an established measure of trait inference. Using a previously validated measure strengthens the conclusions we can draw from the research. This particular measure requires the use of cues that do not explicitly contain the target impression, which limits the possibility of conducting research with nonconstructed stimuli (e.g., posts directly taken from social media). We therefore included alternative assessments, which involved choosing traits to describe an actor and choosing between two actors for a scenario that calls for the trait implied for one of the actors. The outcomes of these alternative measures were consistent with the false-recognitions measure, which offers support for their effectiveness.

Framing a spontaneous-inferences paradigm in a social media setting is another innovation, which can be helpful for future research. Social media provides a realistic setting for research on spontaneous inferences, with possibility to manipulate social context and integrate additional tasks in a smooth way that is intuitive and familiar for the participants.

The experiment in which we investigated impressions during browsing provided evidence for actor-specific trait inferences on scenario-based measure of inferences but had inconclusive results on the recognition measure. Participants were more likely to falsely recognize previously implied traits (as compared to novel traits), regardless of whether they were paired with the person who posted them or another person from the stimulus set. This pattern suggests that people inferred traits from status updates but did not necessarily associate these traits with their corresponding authors. One explanation of this would be that while browsing, people paid more attention to the content itself rather than who posted it. This would be an interesting result, but we cannot firmly assess its robustness, which we acknowledge as a limitation of our present work. The extent to which people form actor-specific inferences while browsing is an important future direction. If future research reproduced the pattern where only novel traits are less likely to be falsely recognized, it would be important to investigate the conditions under which actor-specific inferences do occur.

One limitation of this and prior research is the handling of extraneous characteristics of the stimulus material (e.g., faces). Prior research has included replication conditions with

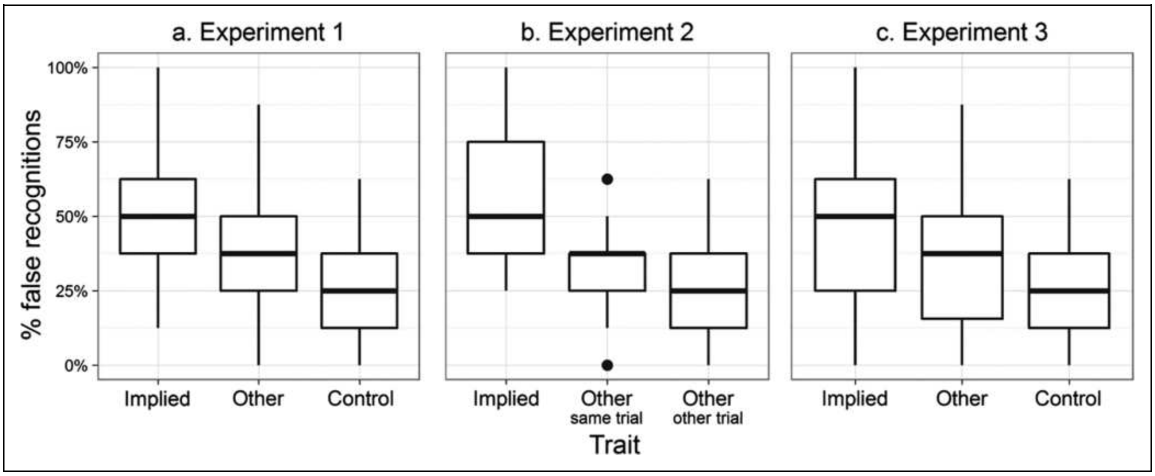


**Figure 2.** Visual summary of results from the false recognition paradigm. Higher number of false recognition rates in the implied-trait condition (relative to the other two conditions) indicate occurrence of spontaneous inferences. Center lines show the medians; box limits indicate first and third quartiles; whiskers extend to the highest and lowest value within 1.5 times the interquartile range; outliers are represented by dots. The data are plotted using ggplot (Wickham, 2009).

differently paired stimuli and shown that the pairing does not influence the overall effects, which led the researchers to drop the replication conditions from future work (Todorov & Uleman, 2003). However, the means of assessing that (through replication conditions which double the sample size) are not optimal. It would be possible to program studies in a way that randomizes stimulus pairs at each run thus reducing extraneous effects to random noise.

Bringing together research on snap social judgment and online impression formation opens up important directions for future work. Clearly, there is more to social media than what our experiments aimed to capture. Under conditions of true information overload, the ability of cues to attract attention might matter more than it did in the present research, thus it will be important to reproduce the effect under even more cognitively demanding conditions. Another direction for future studies we have already mentioned is whether and how spontaneous inferences can help users navigate and maintain their vast online networks. Examining the accuracy of inferences will be important for understanding such interpersonal effects.

## Conclusion

There are many reasons to browse the streams of updates on social media sites—to kill time, to catch up on current events, to have a laugh at a friend's joke. The present research suggests that, without necessarily having the intention to do so, people form impressions of others. These spontaneous processes paint a different picture of what browsing social media might entail. While scrolling down to catch a colleague's most recent pun about conference deadlines, a social media user might also be picking up bits of information that shape her perceptions of people from various corners of her vast online networks.

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### Supplemental Material

The online data supplements are available at http://journals.sagepub.com/doi/suppl/10.1177/1948550616663803.

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## Author Biographies

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# Appendix C

# Spontaneous trait inferences on social media: Report of Experiments 1A and 2A

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We conducted a series of experiments testing the occurance of spontaneous trait inferences in conditions, resembling social media. The main experiments are reported elsewhere. Here we report two additional experiments, which were not included in the paper due to similarity in design and in order to avoid redundancy. Their results are consistent with what is reported in the paper. This is a brief report. For more extensive literature review and discussion, please see the main report: Levordashka & Utz, 2016, June. Main report. Retrieved from osf.io/56sn2

**Brief overview of research background and aims**

Psychological research has shown that even minimal exposure to information can result in meaningful, lasting impressions (Ambady & Rosenthal, 1992; Uleman, Saribay, & Gonzalez, 2008). Such spontaneous impressions can play an important role on social media, as they can allow users to gain awareness of their unprecedentedly large online networks (Donath, 2007; Resnick, 2001). However, the extent to which spontaneous trait inferences are made on social media is not clear.

Existing research has focused on deliberate impressions. Participants are asked to form impressions of others, whose profiles they view at their own pace (e.g., Antheunis & Schouten, 2011; Back et al., 2010; Evans, Gosling, & Carroll, 2008; Pennington & Hall, 2014; Qiu, Lin, Ramsay, & Yang, 2012; Rosenthal-Stott, Dicks, & Fielding, 2015; Westerman, Van Der Heide, Klein, & Walther, 2008). In contrast to deliberate profile evaluation, browsing involves skimming through separate bits of information without particular intentions to form impressions. Even if the encountered posts contain cues similar to those found in profiles, we do not know whether these cues will lead to inferences when people encounter them briefly and without the explicit goal to form impressions.

Although the evidence for spontaneous inferences is substantial (Uleman et al., 2008), the setup of the experiments in which these inferences have been demonstrated differs from social media in important ways, which prevents us from generalizing their effects. The majority of studies on spontaneous trait inferences have used third-party descriptions (e.g., Rim, Uleman, & Trope, 2009; Saribay, Rim, & Uleman, 2012; Todd, Molden, Ham, & Vonk, 2011; Todorov & Uleman, 2002, 2003, 2004), which are particularly powerful in driving impressions (Walther, Van Der Heide, Kim, Westerman, & Tong, 2008). Moreover, the information in laboratory experiments can be of rather extreme nature. Behaviors such as "She threw a chair at her classmate"(Bliss-Moreau, Barrett, & Wright, 2008) or "I kicked [a puppy] out of my way" (Carlston &

Skowronski, 1994; Carlston, Skowronski, & Sparks, 1995; McCarthy & Skowronski, 2011) can be found among the stimulus materials of experiments, but are something rarely seen on the average social media timeline. Another major difference lies in the number of posts people encounter in parallel. Nearly all experiments on spontaneous trait inferences present only one pair of actor and behavioral descriptions a time. Forming a distinct association under these conditions is fairly straightforward. On social media however, where many different actors and behaviors appear in parallel.

Since updates on social media are self-generated and mild in content, it is not clear whether they will be sufficiently powerful as a cue to produce spontaneous inferences. Furthermore, viewing multiple updates in parallel and in "browse" mode might hinder the associative process. These crucial differences prevent us from knowing whether existing psychological research on spontaneous impression formation will generalize to the context of social media. The experiments presented here are part of a research line designed to address this outstanding question.

## Experiment 1A

### Method

**Sample size.** The effect sizes in spontaneous trait inferences experiments, using the false recognition paradigm, are moderately large (e.g., dz = .98 in Todorov & Uleman, 2002, calculated based on t-value and sample size; Lakens 2013). A sample of 16 participants would be sufficient to achieve statistical power of .95 for detecting such an effect size. Since there has been no prior research on the effect of self-generated behavioral descriptions, we have decided on larger sample sizes to ensure power of between .90 and .95 for detecting an effect size dz of between .61 and .68.

**Participants.** Participants were recruited from the student participant pool of a German research institute. Since the stimulus material was presented as content similar to what can be seen on social media and networking sites, some experience with such sites (e.g., Twitter, Facebook) was required for participation. Forty-one participants took part in the study (35 female).

**False recognition procedure** We followed the procedure of the false recognition paradigm (Todorov & Uleman, 2002). Participants saw status updates containing a picture and a short text, which they had to read carefully (learning phase). Each trial consisted of one update displayed for 10 seconds. A total of 36 status updates were presented. One-third of the updates included a personality trait. The remaining updates implied a trait without explicitly mentioning it. In the test phase, the same 36 actors were presented, each paired with a trait word. The 12 actors, whose original description included a trait, were paired with this presented trait. These trials served as fillers and not included in the analyses. The remaining actors were randomly split into three groups and paired with either: the trait implied in their original description (implied-trait condition); the trait implied by the description of another actor (other-trait condition); a novel trait (control condition).

**False recognition measure.** During the test phase participants were asked to indicate as quickly as possible whether a word was "old" (i.e., presented in the update an actor originally posted) or "new". The correct response to all trials was "new" and responses "old" were coded as errors (false recognitions). False recognition rates were compared across conditions. Response times to correct trials were also recorded and compared across conditions.

**Direct assessment of impressions.** In addition to the false recognition paradigm, participants were asked to evaluate some of the actors ($n$ = 12 per participant) from the learning phase. On each trial they were shown a face, paired with two traits: the trait implied by the status update and another trait of the same valence. This assessment of impressions served as a direct measure of trait inference.

**Memory of stimuli.** We measured memory for stimulus materials in a recall task. Participants saw six faces and were asked to type their corresponding updates. The responses were coded by a research assistant unaware of the design and hypotheses. The scale for accuracy was: 0 = *no response*, 1 = *not at all accurate*, 2 = *accurate meaning; mistakes in wording*, 3 = *mostly accurate*, 4 = *accurate*. We included an additional measure, checking whether participants recalled the content of updates, but paired them with the wrong targets. If a participant's response was a somewhat accurate recollection of one of the stimulus sentences but not that of the target face, the response was coded as mistaken target.

**Excluded cases.** For each measure in the study, scores over three standard deviations above or below the sample mean were excluded as outliers. This decision was made prior to data collection. There were no outliers on te false recognition measure and one outlier on the response times measure. This person was excluded from all analyses.

Additionally, we excluded five participants from analyses involving response times. Response times were computed for correct trials per condition. Four participants made no correct responses in the implied-trait condition; and one participant -- in the control condition. Since we could not compute response times, we excluded these participants from the analysis of response times (but not any of the other analyses).

For the direct assessment of impressions, participants 1 to 17 had to be excluded from the analysis due to a technical error during the first day of data collection. Participants were originally instructed to use the left Alt and right Control key to submit their responses, but many reported becoming confused and using the right Control and left Alt instead. The answer keys were then recoded to 'X' and 'M', which resolved the issue. The difference in allowed responses is also visible in the raw data, which is available upon request.

## Results

Participants made considerably more mistakes when an actor's face was paired with the trait implied for this actor (implied-trait condition; $M$ = 0.52, $SD$ = 0.31), as compared to a trait implied for another actor (other-trait condition; *M* = 0.22, *SD* = 0.21) or a novel trait (control condition; *M* = 0.21, *SD* = 0.25). There was no significant difference between the other-trait and control conditions.

Table 1.

*Results of dependent-samples t-tests comparing false recognition rates across conditions.*

| Difference | df | t | *p* (two-tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| implied-other | 39 | 5.25 | < 0.001 | 1.12 [0.64;1.63] |
| implied-control | 39 | 5.23 | < 0.001 | 1.09 [0.62;1.59] |
| other-control | 39 | 0.5 | 0.621 | 0.07 [-0.2;0.33] |

Average response times to correct trials ranged between 0.9 and 6.3 seconds (*M* = 2.58, *Mdn* = 2.33, *SD* = 1.15). The data violated assumptions of normality. We performed a log10 transformation on the row data (RTs per trial). To avoid negative values, we added 1.0 to all values prior to the transformation. Following the transformation, the data no longer violated the assumptions of normality and equal variances (Shapiro Wilk's *p*s > 0.01; Levene's test *p*s > 0.28). Response times to correct trials were longer than response times to control trials (Table 2). These differences are in line with the idea that providing a correct response was more difficult for implied traits.

Table 2.

*Results of dependent-samples t-tests comparing RT to correct trials across conditions.*

| Difference | df | t | *p* (two-tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| implied-other:same trial | 33 | 2.77 | 0.009 | 0.26 [0.07;0.47] |
| implied-control:other trial | 33 | 2.83 | 0.008 | 0.27 [0.07;0.47] |
| other:same trial-control:other trial | 33 | 0.39 | 0.697 | 0.03 [-0.12;0.18] |

Note. Reported means are back-transformed.

More than half of the respones were either entirely absent (47%) or inaccurate (14%). However, there were also many cases of accurate recalled status updates (38%). This indicates that participants had memorized some of the updates.

The occurrence of spontaneous inferences was also apparent when participants were asked to evaluate the actors from the learning task. Participants selected the trait implied about the an actor over a trait implied by another actor NaN% of the time, which was significantly higher than chance (95%CI [0,1], $p$ = 1).

## Discussion

The results of this experiment show that the content typically encountered on social media - brief, self-generated, and mild - can result in spontaneous trait inferences. Trait inferences were evident in the number of mistakes participants made: They were more likely to falsely recognize a trait as having been previously presented in an actor's status update when the trait was implied by the status update. In a separate task, when asked to evaluate an actor, participants were more likely to select the trait implied by the actor's status update versus another trait of similar valence. However, our memory measure revealed that in nearly half of time, participants were able to recall the content of an actor's status update, which prevents us from knowing whether the results of the latter, direct evaluation measure, were driven by trait inference or by stimulus recall. To reduce the rate of memorization in the actual experiment, we reduced the presentation time from 10 to 5 seconds per trial.

In the present experiment, we showed only one update at a time and the possibility remains that if information about different actors is presented at once, there will not be clear associations and person-specific inferences. The following experiment was designed to test address this concern. Although our main aim was to test whether the effect occurs with a larger number of stimuli, we began by showing 2 updates at a time. The experiment was thus similar to the experiments conducted by Todorov and Uleman (2004).

# Experiment 2

## Method

### Participants and procedure.

Thirty-four participants took part in the study. The procedure, stimuli, and measures were similar to those in Experiment 1, with the exception of how we presented the stimuli. Instead of seeing one status update at a time, participants saw two updates in parallel. There were 16 trials, each consisting of two status updates. Apart from the implied-trait condition, there were two comparison conditions: other (same trial), where faces were presented with the trait implied by the other status update in the same trial and control (other trial), with traits of status updates from other trials.

The free recall tasked was scored as described in Experiment 1A. Inter-coder reliability was estimated on 20% of the responses, for which ratings were obtained from two independent coders. There was high consistency (ICC_accuracy = 0.93, 95%CI [0.83,0.97], ICC_mixed = 0.68, 95%CI [0.37,0.86]).

## Results

Participants made considerably more mistakes when an actor's face was paired with the trait implied for this actor (implied-trait condition; $M$ = 0.53, $SD$ = 0.21) as compared to a trait implied for another actor from the same trial (*M* = 0.31, *SD* = 0.2) or from another trial (*M* = 0.32, *SD* = 0.19). There was no significant difference between the two control conditions.

Table 3.

*Results of dependent-samples t-tests comparing false recognition rates across conditions.*

| Difference | df | t | *p* (two-tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| same-other | 34 | 6.26 | < 0.001 | 1.03 [0.64;1.47] |
| same-control | 34 | 5.45 | < 0.001 | 0.99 [0.57;1.45] |
| other-control | 34 | -0.4 | 0.692 | -0.05 [-0.32;0.21] |

Average response times to correct trials ranged between 1.09 and 4.18 seconds (*M* = 2.25, *Mdn* = 2.1, *SD* = 0.75). The data violated assumptions of normality. We performed a log10 transformation on the row data (RTs per trial). To avoid negative values, we added 1.0 to all values prior to the transformation. Following the transformation, the data no longer violated the assumptions of normality and equal variances (Shapiro Wilk's _p_s > 0.5; Levene's test *p*s > 0.11). One participant made no correct responses in the other trait, same trial condition. Response times to correct trials could not be computed and we excluded participants in order to keep a balanced design. There were no significant differences between conditions (all *p*s > 0.294).

Table 4.

*Results of dependent-samples t-tests comparing RT to correct trials across conditions.*

| Difference | df | t | *p* (two-tailed) | Hedges' *g* [95% CI] |
|---|---|---|---|---|
| same-other | 33 | 0.73 | 0.468 | 0.11 [-0.19;0.41] |
| same-control | 33 | 1.07 | 0.294 | 0.17 [-0.15;0.5] |
| other-control | 33 | 0.52 | 0.605 | 0.07 [-0.2;0.35] |

As in Study 1, recall of the status-update sentences was low. On the majority of trials, participants provided no response (40%) or a highly inaccurate response (32%). There were some cases where a sentence from the stimulus set was recalled but reported for the wrong target person (19%), which shows that participants recalled more than their raw memory scores suggest. Nevertheless, the overall recall was sufficiently low.

Despite having poor recall of the seen updates, when asked to evaluate an actor, participants chose the implied trait another trait of the same valence 74% of the time, which was significantly higher than chance

(95%CI [0.68,0.8], $p < .0001$). This result is consistent with our hypotheses and the pattern observed in Experiment 1.

### Discussion

Experiment 2 provided evidence that the simultaneous presentation of status updates can result in distinct, actor-specific inferences. Participants were more likely to falsely recognize an implied trait as having been previously presented, which indicated that they spontaneously inferred the trait. They were also more likely to associate an actor with the trait implied by this actor's update, without necessarily being able to recall the update. We did not find the expected differences in response times. Although the differences reached the conventional levels of significance, they were small, opposite of what was expected, and inconsistent with the results of the prior experiment where no effects were found.

Unique to this experiment is the demonstration that when participants viewed updates simultaneously, the traits they inferred from each update were distinctly associated with the author of the update and not with the other person whose picture and update they viewed at the same time. However, the experimental setup does not rule out the possibility that browsing poses a boundary condition to this association. We therefore conducted a third experiment, in which participants browsed through the updates at their own pace in a setup that closely resembled social media.

### General discussion

For the general discussion of the research, please refer to the publication.

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## Appendix A

Table 1

*Descriptive statistics and zero-order correlations.*

| | Means | SD | 2 | 3 |
|---|---|---|---|---|
| **Experiment 1A** | | | | |
| 1. False recognitions | 0.32 | 0.18 | 0.16 | -0.36* |
| 2. Respone times | 2.64 | 1.17 | | 0.37 |
| 3. Memory | 1.82 | 0.72 | | |
| **Experiment 2A** | | | | |
| 1. False recognitions | 0.39 | 0.17 | -0.06 | 0.35 |
| 2. Respone times | 2.23 | 0.67 | | 0.31 |
| 3. Memory | 1.12 | 0.46 | | |

# Appendix D

# Ambient awareness of who knows what: Spontaneous inferences of domain expertise

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**Abstract**

Being able to recognize the expertise of others (who knows what) is essential for knowledge exchange. A prominent idea among media and organization scholars is that browsing social media fosters such awareness, because people spontaneously register various cues to others' interests and expertise they encounter online (ambient awareness). However, the central idea that ambient awareness develops without effort or intention has never been tested. In the tradition of spontaneous inferences research, we examined whether inferences of domain expertise are indeed spontaneous. In two experiments, participants inferred actors' implied expertise after reading (Experiment 1; $N = 91$) or skimming through (Experiment 2; $N = 269$) domain-implying social media posts. Domain inferences under low attentiveness (skimming) were moderated by number of cues and participants' own interests. By extending psychological research on spontaneous inferences to domain expertise, we provide a foundation for research into ambient awareness and the informational benefits of social media.

*Keywords:* Social Perception, Social Cognition, Human-computer interaction, Human Information Storage, Organizations

**Ambient awareness of who knows what: Spontaneous inferences of domain expertise**

Ambient awareness refers to the idea that people can get to know who is who and who knows what in their online social networks by regularly skimming social media updates, without having to pay particular attention or exert any exceptional effort (Leonardi, 2015; Levordashka & Utz, 2016a; Thompson, 2008). The concept has received substantial attention in the communication and organization literature because awareness of who knows what is fundamental to successful information exchange processes (Austin, 2003; Wegner, 1987). However, this awareness is not that easy to achieve in mediated communication (Fulk & Yuan, 2013; Leonardi, 2015; Leonardi & Meyer, 2015). Social media have been praised highly for their potential to help people profit from the large, diverse, and geographically dispersed networks that digital technologies make possible (Chui et al., 2012; Donath, 2007). First studies show associations between social media use and informational benefits (Leonardi & Meyer, 2015; Utz, 2015) and ambient awareness has been at the forefront of theories as to how these benefits come about. However, the central idea of ambient awareness that information about who knows what is inferred spontaneously, without effort or deliberation, has not been tested. This proposition is crucial, because given the size and complexity of social networks and the sheer amount of information on social media, a deliberate process would be far less potent and efficient than this spontaneous process. Conceptual support comes from psychological research on snap person judgments and spontaneous inferences (Ambady & Rosenthal, 1992; Uleman, Adil Saribay, & Gonzalez, 2008), but there is no evidence that these phenomena extend to information about domains of expertise (who knows what). In the research presented here, we tested whether awareness of others' domains of expertise can develop spontaneously, that is, without deliberate intention and effort, in the course of browsing social media. By extending psychological research on spontaneous inferences to domain expertise in the context of social media, we seek to provide a foundation for research into the informational benefits of social media.

Social media is a broad term used to describe communication technologies which allow users to create and disseminate content publicly or to a specified group (network, community). This includes popular services like Twitter, Facebook, and LinkedIn, but also company-internal enterprise software. Social media enable lightweight communication, such as declaring and displaying social relationships (e.g., "following", "friending"), broadcasting content to wide audiences, easily commenting on, re-sharing, and reacting to others' content. Using social media results in a development of awareness (Rice et al., 2017; Treem & Leonardi, 2012)/ While awareness is already considered to be one of the affordances of social media (Rice et al., 2017), less is known about the process through which it develops. Information on social media is typically brief, momentary, and delivered to users in real time, resulting in a stream of disconnected updates from different people. As a result, single pieces of information are not particularly informative and rarely given more than a passing glance. Therefore awareness via social media stems from the accumulation of fragmented personal information (Hampton, Lee, & Her, 2011; Leonardi, 2015; Levordashka & Utz, 2016a).

Theoretical support for the idea of ambient awareness comes from psychological research on spontaneous inferences from brief instances of behavior (Uleman et al., 2008). This shows that people spontaneously extract potentially valuable information, even in conditions of superficial processing and under high cognitive or information load. Research has found this to be the case for different kinds of information, including traits, values, and, more recently, social roles (Chen, Banerji, Moons, & Sherman, 2014). The explanations behind spontaneous inferences in psychology revolve around the idea that some information is inherently and fundamentally valuable (Moskowitz & Olcaysoy Okten, 2016; Uleman et al., 2008). For example, knowing others' traits and goals helps people judge whether they would attack or protect them, which is likely not the case when it comes to knowing whether someone is a programmer or a photographer. Implicated in ambient awareness, however, are exactly such inferences of domains of knowledge, which have never been demonstrated and can be considered unlikely. It is important to note that we consider domains of expertise (e.g., who is a programmer) rather than degree of competence (e.g., who is the better programmer).

Moreover, while conceptually related, spontaneous trait inferences from behavior differ from inferences via social media in important ways that prevent direct generalization. Recent work has shown that the effect generalizes to some extent but has also highlighted some limitations (Levordashka & Utz, 2016b). Namely, while evidence for spontaneous inferences was found for multiple stimuli presented at once, the effect was less pronounced when people browsed a timeline at their own pace (as opposed to seeing the posts for a fixed amount of time). Existing work on the topic is therefore not sufficient to ensure that awareness via social media can develop spontaneously.

Evidence for ambient awareness and its potential role in information exchange comes from a number of recent studies. Leonardi (2015) found that after using social media, employees had better awareness of who knows what in their department. The participants reported both the frequency with which they "happened to notice" versus "spent time carefully reading" information about others. It was the process of "happening to notice" that better predicted subsequent awareness. Another study found that people were more satisfied with knowledge transfer, if they used social media to find out more about their communication partners before actually approaching them (Leonardi, 2015). Surveys revealed that browsing was related to self-reported familiarity with the hobbies and profession of people known only through social media (Levordashka & Utz, 2016a).

These studies highlight the importance of ambient awareness but fail to provide any convincing test of the major premise that awareness arises without deliberate effort or intention. Surveys measure user activity and correlate it to perceived levels of awareness. However, they are not able to validate the accuracy of people's perceptions. Studies done within organizations could validate the accuracy of awareness, but could not rule out the influence of prior acquaintanceship, face-to-face interactions, and motivation, since they were conducted in a workplace context where people interact frequently and topics related to expertise are particularly salient.

In the research presented here, we seek to answer the question: Can awareness of domain expertise (who knows what) develop spontaneously and efficiently in the course of browsing. In two experiments, participants (observers) browsed social media posts, some of which contained cues to the expertise of the people who ostensibly posted them (actors). We used two measures to assess whether the observers inferred the actors' expertise from the posts. There was no mention of expertise inference or impression formation in the instructions, therefore the inferences observers made could be considered spontaneous.

In the first experiment, we focused on the type of information and mode of presentation. As we previously outlined, there has been no prior research evidence that people spontaneously infer domains of expertise in the same way they infer traits, values, or goals. We adapted an existing trait-inference paradigm (Todorov & Uleman, 2002) using domain-implying cues (e.g., "Front-end developer aka JavaScript wizard also HTML5/CSS3. Hire me!" suggesting knowledge in the domain of programming). In addition, since prior work on trait inferences in social media suggested that trait inferences are weaker when people browsed a timeline, we compared inferences under different modes of presentation: self-paced viewing of a single stimulus pair versus browsing all stimuli on a timeline. We hypothesized that participants would infer information about actors' domains of expertise after reading a short social media update and without being instructed to do so (H1), and that this effect might be weaker or absent when people browse on a timeline (H2).

In the second experiment, we used instructions that further diminished attentiveness. We anticipated that in conditions that caused low attentiveness, participants would be less likely to notice individual posts. We therefore included actors with multiple posts that implied the same domain. Our hypotheses were that domain inferences would occur under low attentiveness (H3), but the effect might weaker or absent for actors with single cues (H4). We also explored the possibility that observers might attend to actors' domains to a greater extent if they were additionally motivated to do so. We therefore manipulated the expectation of an upcoming domain-related task and tested whether this resulted in stronger inferences (H5). Hypotheses 4 and 5 address potential moderating factors, which, if supported would speak against the spontaneity and efficiency of the process.

We additionally examined whether exposure to different types of posts would influence the observers' impressions of the actors' approachability and competence. Although not directly linked to domain inferences, impressions play an important role in information exchange. Based on the mere exposure literature (Bornstein, 1989), we hypothesized that participants would be more likely to judge people seen multiple times as more approachable than people seen only once (H6). In both experiments we investigated the potential role of other factors, including the participants' own domains of interest and their self-reported interest in the posts.

## General method

We collected data online and convenience samples recruited through the participant pool Prolific. The experiments took up to 15 minutes to complete, and each participant received 1.3 GBP in payment. Participants were informed about the procedure, potential risks, and benefits but not the exact purpose of the study. Instead, they were told that the study was about "how people process the information they see in social media". At the end of the study they were debriefed and provided with the opportunity to withdraw their data using an anonymous I.D. Sample size was planned to ensure a power of at least 80% to detect a small to medium effect (Cohen's d = .40). The effect size estimate was based on prior studies using similar design (Todorov & Uleman, 2002; Levordashka & Utz, 2016).

The experiments were preregistered. We report all data exclusions, manipulations, and measures. The pre-registration materials, data, and analysis scripts are available at: https://osf.io/mfb4z/?view_only=b1eed1bea0ba4fe3a486eb0967ab5184 [Anonymized link].

### Procedure

**Learning phase.** In the learning phase, participants saw actors paired with cues that implied certain domains of expertise without mentioning them explicitly (e.g., "Front-end developer aka JavaScript wizard also HTML5/CSS3, and PHP. Hire me!" suggesting knowledge in the domain of programming). Participants were only instructed to read or browse, there was no mention of impression formation. The exact instructions varied between experiments and are reported in the individual methods sections. The learning phase was always self-paced, that is, participants decided how much time they wanted to spend reading the posts.

**Stimuli.** The complete list of domains and domain-implying sentences can be seen in Supplementary Materials Table S1. We selected 10 domains (Teaching, Design, Management, Programming, Biology, Architecture, Photography, Advertising, Psychology, Finance) with the general criteria that they were not too specific or obscure and reasonably distinctive. Research assistants collected and rephrased social media posts that implied or mentioned each of the domains. There were 5 posts per domain. Posts that did not imply a domain were considered "neutral". We had a pool of 20 neutral posts. We selected 40 faces (50% female) of similar attractiveness, competence, and memorability from the Bainbridge, Isola, & Oliva (2013) database (ratings are included in the database). The stimuli were presented in the form of social media posts, containing a face (the post's author) and a sentence (the post's content). To avoid potential confounds related to participants' stereotypes of certain domains, we did not use a fixed set of stimuli but instead used an algorithm to generate a novel set of stimuli on each run. In this way, each participant saw a particular domain with a different combination of face, name, and sentence. We recorded information for each cue, including actor's gender and the domain implied by their social media post.

**Probe recognition task.** After seeing all of the posts, the participants completed a forced-choice probe recognition task, adapted by Todorov and Uleman (2002), which assesses inferences indirectly. Participants saw each actor from the learning phase, paired with a word, and had to indicate whether this word was mentioned in the sentence they had previously seen with the actor. Each actor whose cue implied a domain was presented twice: Once with the domain word implied by the cue (same/match) and once with the domain-word implied for another actor (other/mismatch). In addition, all of the actors whose posts did not imply any domain (neutral) were presented with a word that had been part of the sentence from the learning phase.

**False recognition measure.** In each trial of the probe recognition task, participants indicated whether the word presented next to an actor's face was present in the sentence they had previously seen with the actor ('old') or whether it was a new word ('new'). All actors for which a domain had been implied were presented with a word that had not appeared in the sentence, therefore responses 'old' were always incorrect (false recognition). Prior studies have consistently shown that after seeing a number of actor-cue pairs, people were more likely to falsely recognize implied information as having been previously presented, when this information is paired with the actor whose cue implied it (same/match), as compared to another actor (other/mismatch). Therefore, a pattern where more mistakes were made on matched versus mismatched trials indicated that participants made actor-specific inferences.

**Domain identification task.** The false recognition task was followed by a direct assessment of domain identification, where participants had to identify each actor's domain of expertise from a list of 9 domains, with an option to skip the question (non-response). Domain identification was considered correct when the response participants provided in the domain recognition measure matched the one implied by the actor's cue in the learning phase. Separately, we coded whether participants selected 'skip' rather providing an answer (non-response).

**Additional measures.** At the end of the study, participants identified their own domains of interest/expertise from a list of all domains included in the study, reported how frequently they use social media, and estimated their level of attentiveness throughout the study (ranging from 0 = "answered all questions carefully" to 4 = "responses were mostly random"). We recorded the time they spent reading posts in the learning phase, as well as their total study duration. Demographic information, including gender, age, and employment status was retrieved from the participant recruitment platform.

**Randomization.** Within each block (task), trials were randomized on each run (i.e., different order for each participant). The only exception was the follow-up questions, which always appeared in the same order.

**Exclusion criteria.** Participants who reported low attentiveness ("responses were mostly random") were excluded. For each experiment, we conducted pretests to estimate the shortest completion time that could be considered meaningful. A research assistant was instructed to complete the study as quickly as possible, skimming through questions but not entirely skipping them. Since in the learning phase participants were instructed to read the posts at their own pace, we subtracted the duration of this phase and excluded participants based only on the time they spent on the remaining phases.

## Experiment 1

### Method

The experiment had a mixed-design with one between-subjects condition (presentation: single post per page vs. all posts on a timeline), a repeated-measures task with within-subject manipulation (false recognition paradigm; probe type: same domain vs. other domain), and a one-sample accuracy task (domain identification). The experiment was preregistered. All data and materials are publicly available. We collected responses from 110 participants.

**Excluded cases.** Based on our pretest, the shortest meaningful completion time (excluding the learning phase) was 1.75 minutes. As planned, we excluded participants whose study duration was under this threshold ($n$ = 14). Two additional participants were excluded for reporting low attentiveness ("responses were mostly random"). These exclusion criteria were planned and preregistered. In addition, due to unforeseen errors in the experimental code, certain trials in the probe recognition task were not displayed and resulted in missing data. The missing trials occurred at random. This error affected 23 participants. For our dependent measure, each participant responded to 9 trials, which were then aggregated to a mean score. From the participants affected by the error, we retained data from those who had responded to at least three trials ($n$ = 20). We analyzed data from 91 participants.

**Stimuli and manipulations.** Each participant saw a unique set of 9 domain-implying and 9 domain-neutral posts in random order. Participants were randomly assigned to either viewing one post at a time ($n$ = 48) or all posts on a timeline ($n$ = 43).

## Results

**Sample descriptives.** Demographic information was retrieved separately from the Prolific participant pool. The sample consisted of 25 females and 59 males (gender information for 7 participants was missing). The mean age was 28 (*SD* = 8; 7 missing). Roughly half of the participants were employed full time (48%) and another 30% were employed part-time or were unemployed and seeking.

One participant took 58.6 minutes to complete the study. The remaining responses ranged from 3.4 to 20.6 minutes (*Median* = 7.5, *Mean* = 8.6, *SD* = 4.1). On average, participants took (*SD* = 1.1; *Median* = 1.5) minutes to read the 18 posts.

**False recognitions.** The data were analyzed and plotted in R (R Core Team, 2016; Wickham, 2009). The analysis of false recognition was performed only on domain-related trials (responses to actors whose posts contained domain cues). Neutral trials served as fillers and were removed. The trials within each within-subject condition were aggregated to a mean score. This is an established analysis strategy is commonly adopted with the false-recognition paradigm (e.g., Todorov & Uleman, 2002; Chen et al., 2016). We used linear mixed models fit by maximum likelihood (Bates, Mächler, Bolker, & Walker, 2015). Model summaries in Table 1.

First, to determine the effect of probe type (same versus other) we compared an intercept only model (M1) with a model including probe type (M2) and a model with interaction between probe type and presentation (M3). The only significant improvement from the intercept-only model (M1) was adding probe type (M2), $\chi^2 = 17.67$, $p < .0001$ (all other $p$ s > 0.506). The main effect of probe type was such that participants made more mistakes on same-domain ($M = 0.52$, $SD = 0.22$) versus other-domain trials ($M = 0.39$, $SD = 0.23$; Hedges' g = 0.4 95%CI [0.11,0.7], $p < .0001$), regardless of presentation. That is, participants were likely to think that they had seen a certain domain-related word in a sentence that had merely implied it, from which we conclude they spontaneously inferred the actors' implied domains of expertise (H1).

Table 1

*Model summaries for effects of probe type and presentation on false recognition rates*

| | *DV: False recognitions* | | |
|---|---|---|---|
| | M1 | M2 | M3 |
| PT | | -0.13$^{***}$ | -0.16$^{***}$ |
| | | (-0.18, -0.07) | (-0.24, -0.08) |
| PRES | | | -0.04 |
| | | | (-0.13, 0.05) |
| PT * PRES | | | 0.07 |
| | | | (-0.05, 0.18) |
| Constant | 0.45$^{***}$ | 0.52$^{***}$ | 0.53$^{***}$ |
| | (0.42, 0.49) | (0.47, 0.56) | (0.47, 0.60) |
| Observations | 182 | 182 | 182 |
| Log Likelihood | 6.54 | 15.37 | 16.05 |
| Akaike Inf. Crit. | -7.07 | -22.75 | -20.11 |
| Bayesian Inf. Crit. | 2.54 | -9.93 | -0.88 |

*Note:* $^{**}p < .05$, $^{***}p < .01$. PT=Probe type, PRES=Presentation.

Originally, we had planned to analyze the study using a repeated-measures ANOVA, but changed the analysis strategy due to the unbalanced group sizes (there were 5 more participants in the single-post condition). To ensure that the initial analysis plan yields similar results, we performed two repeated-measures ANOVA: one after excluding the last 5 responses in the single-post condition and one after excluding the first 5 (Table S3 in the supplementary material). The results of both analyses corresponded to what we had found in the mixed models: main effect of probe type (*p*s < .001; all other *p*s > .182).

**Domain identification.** On average, people skipped items 22% of the time. They did so significantly less often for actors whose posts contained domain cues (16%), versus actors whose posts were neutral (27%), $\chi^2$ (1, $N$ = 1412) = 27.11, $p < .0001$.

Since participants were asked to select from 10 options (9 domains and "skip"), we considered the probability of correctly guessing the implied domain to be 10%. Results are displayed in Figure 1.

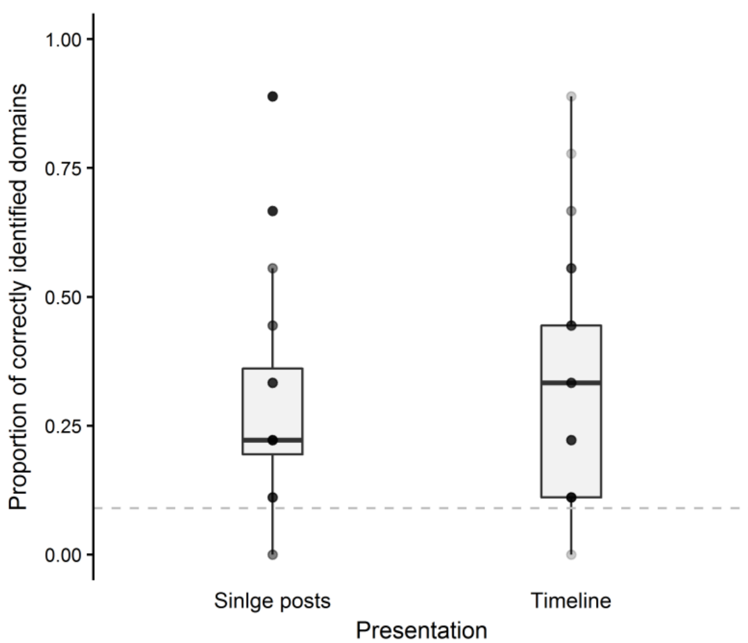


*Figure 1.* Accuracy of domain identification as a function of presentation. Horizontal line represents chance-level accuracy.

We used exact binomial tests to compare the observed number of correct responses to what could be expected by chance. In both conditions, participants' responses were significantly higher than chance at recognizing the domains implied by actors' posts (single post condition: 30% of successful recognition, 95%CI [0.25,0.34], $p < .0001$; timeline condition: 33% of successful recognition, 95%CI [0.28,0.38], $p < .0001$). There was no significant difference in domain identification accuracy between the two presentation conditions, $t(78) = -0.703$, $p = 0.48$. Thus, the instances of correctly identifying an actor's domain of expertise were higher than chance regardless of presentation. In line with our other dependent variable, this suggests that the observers formed impressions of the actors' expertise without having been instructed to do so (H1), regardless of how the posts were presented (H2).

## Experiment 2

In this experiment, we examined the effect under lower levels of attentiveness (i.e., skimming). Furthermore, we explore the role of factors such as observers' own domains of interest, which might become increasingly relevant under low attentiveness.

### Method

The procedure and primary measures are as described in the general method. Participants were instructed to "browse through the posts" rather than "carefully read" the posts. We introduced two factors: number of cues per actor (within-subjects) and implied goal (between-subjects) and measured participants' impressions of the targets in a forced-choice task. The experiment had a 2 between (implied goal; no goal) by 2 within (single versus multiple domain cues) mixed-design.

We had planned to collect data from 200 participants in order to ensure 95% power for detecting a small effect size (Cohen's d = .40) for a main effect of probe type and a 80% power of detecting a significant interaction between probe type and number of cues in each between-subject condition. After reaching the planned sample of participants, we became aware that due to an error in the randomization procedure, all of the participants had been assigned to the no-goal condition. In the same interval of time on the following day, we collected additional responses, all of which were in the remaining implied-goal condition. Therefore, the assignment to the between-subjects condition was not random. Our final sample consisted of 304 responses (195 in the no-goal and 109 in implied-goal condition).

**Excluded cases.** As described in the general method, we conducted pretests to estimate the shortest meaningful completion time that could be considered meaningful. The time it took to complete all of the tasks, excluding the learning phase, was 1.8 minutes. As planned, we excluded participants whose study duration (excluding the learning phase) was under this threshold (*n* = 23). On the self-reported measure of attention, 11 participants reported low attention ("Your responses were mostly random") and were excluded. One person appeared to have completed the study twice and we excluded their second set of responses. In total, we excluded 35 respondents and analyzed data from 269 participants (174 in the no-goal and 95 in implied-goal condition).

Another potential exclusion criterion was a manipulation check, where participants were asked to identify the instructions they had received at the beginning of the study. Only 48% of the respondents were able to do that successfully. As specified in the preregistration, in this case we did not use the manipulation check as an exclusion criterion but as a factor in a set of exploratory analyses.

**Stimuli and manipulations.** Each participant saw a unique set of 40 posts from 16 different actors in random order. The posts of 8 actors implied expertise domains. Half of these 8 actors had four different posts, each implying the same domain (multiple-cues condition) and four had a single post (single-cue condition). The remaining 8 actors had domain-neutral posts. Again, half of these had four posts and half had a single post. All participants received the following instructions: "You are about to see a number of social media posts. Browse through the posts at your own pace and mark the ones you consider interesting using the corresponding Like (thumbs-up) buttons." For participants in the implied-goal condition ($n$ = 109) this was followed by the sentence: "Afterwards you will work on a task that involves selecting experts who could provide a second opinion on a series of topics. Specific instructions will follow." At the end of the study, we included a manipulation check, in which we asked the participants to identify the instructions they had received, among 4 similar sounding instructions.

**Impressions measure.** We measured participants' impressions of the actors' approachability and competence with a series of forced-choice trials. On each trial participants saw two faces and had to choose the face they consider more approachable or competent, respectively. We compared the following groups: a) one neutral versus multiple neutral cues; b) one domain versus multiple domain cues; c) multiple neutral versus multiple dominant cues. For each two groups, each of the 4 actors in one group was paired with one of the 4 actors in the other group. All pairs were of the same gender. This resulted in 12 trials per judgment block (approachable, competent), randomized within the block. Definitions of approachability and competence were provided before the respective blocks were presented.

## Results

**Sample descriptives.** The remaining sample consisted of 176 females and 18 males (21 missing), with a mean age of 28 ($SD$ = 10). On average, participants took 10.7 ($SD$ = 4.9), minutes to complete the study and 2.9 (*SD* = 4.9) minutes to read all posts. Most participants were employed full-time (53%), part-time (21%) or were unemployed and seeking a job (12%).

**False recognitions.** As in Experiment 1, neutral-cue (i.e., filler) trials were removed, the four domain-cue trials within each within-subject condition were aggregated to a mean score, and we used linear mixed models with random intercepts for participants (Table 2)

*Table 2*

*Model summaries for effects of probe type, number of cues, and implied goal on false recognition rates*

| | *DV: False recognitions* | | | | |
|---|---|---|---|---|---|
| | M1 | M2 | M3 | M4 | M5 |
| PT | | $-0.14^{***}$ | $-0.04^{*}$ | $-0.14^{***}$ | $-0.05^{*}$ |
| | | (-0.17, -0.11) | (-0.09, 0.002) | (-0.18, -0.10) | (-0.10, 0.01) |
| NC | | | $0.18^{***}$ | | $0.16^{***}$ |
| | | | (0.13, 0.22) | | (0.10, 0.21) |
| PT * NC | | | $-0.19^{***}$ | | |
| | | | (-0.25, -0.13) | | |
| IG | | | | 0.01 | -0.02 |
| | | | | (-0.05, 0.06) | (-0.09, 0.05) |
| NC * IG | | | | | $-0.18^{***}$ |
| | | | | | (-0.26, -0.10) |
| PT * IG | | | | | 0.05 |
| | | | | | (-0.04, 0.14) |
| PT * NC * IG | | | | 0.01 | 0.02 |
| | | | | (-0.06, 0.07) | (-0.07, 0.11) |
| Constant | | | | | -0.03 |
| | | | | | (-0.16, 0.10) |
| Constant | $0.49^{***}$ | $0.56^{***}$ | $0.47^{***}$ | $0.56^{***}$ | $0.48^{***}$ |
| | (0.47, 0.51) | (0.54, 0.59) | (0.44, 0.51) | (0.53, 0.59) | (0.44, 0.52) |
| Observations | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 |
| Log Likelihood | -205.61 | -172.21 | -142.50 | -172.08 | -141.63 |
| Akaike Inf. Crit. | 417.23 | 352.42 | 297.00 | 356.15 | 303.26 |

*Note:* $p < .05$, $^{***}p < .01$. PT=Probe type, NC=Number of cues, IG=Implied goal.

To determine the effect of probe type (same versus other) we compared an intercept-only model (M1) with a model including probe type (M2). Including probe type significantly improved the model fit ($\chi^2 = 66.8$, $p < .0001$), indicating significant main effect of probe type, which indicates that the participants inferred actors' domains of expertise (H3).

To test the effect of number of cues, we compared the probe-type-only model (M2) to a model including the interaction between probe type and number of cues (M3). The interaction improved the model fit substantially ($\chi^2 = 59.42$, $p < .0001$). The interaction qualified the effect of probe type, indicating that trait inferences occurred only for actors of whom the participants had seen multiple posts (Figure 2).

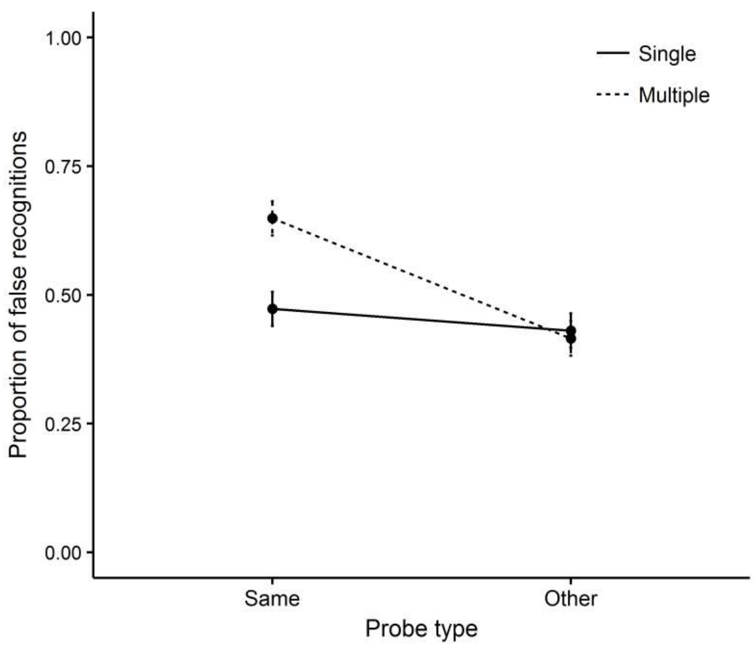


*Figure 2.* Interaction between probe type and number of cues

For actors with multiple-domain cues, participants made more mistakes on trials where actors were presented with the domain implied by their posts (same; *M* = 0.65, *SD* = 0.29), as compared to trials on which actor were presented with other domains (other; *M* = 0.42, *SD* = 0.28; Hedges' g = 0.52 [0.35,0.69]). For actors with single-domain cues, participants made similar number of mistakes regardless of probe (same: *M* = 0.47, *SD* = 0.28; other: *M* = 0.43, *SD*

= 0.27; Hedges' g = 0.11 [-0.06,0.28]). Thus trait inferences only occurred for actors who had multiple domain cues (H4).

A model with implicit goal and probe type interaction (M4) did not improve model fit over probe type ($\chi^2 = 1.75$, $p = 0.782$), indicating that implicit goal had no effect on trait inferences (H5). We additionally looked at whether the three-way interaction model (M5) had better fit than our best model (M3), and it did not ($p = 0.782$).

**Domain identification.** On average, people skipped items 25% of the time. They did so significantly less often for actors whose posts contained domain cues (21%) versus actors whose posts were neutral (30%), $\chi^2$ (1, N = 1412) = 37.98, p < .0001. The analysis of domain identification was analogous to that of false recognition (Model summaries in Table 3). The number of cues improved the model fit over an intercept-only model ($\chi^2 = 62.96$ , p < .0001) whereas implied goal did not ($\chi^2 = 0.06$ , p = 0.806).

Table 3

*Model summaries for effects of number of cues and implied goal on domain identification accuracy*

| | *DV: Domain Identification* | | | |
|---|---|---|---|---|
| | M1 | M2 | M3 | M4 |
| NC | | $0.16^{***}$ | | $0.16^{***}$ |
| | | (0.13, 0.20) | | (0.11, 0.21) |
| IG | | | 0.01 | 0.0000 |
| | | | (-0.05, 0.06) | (-0.07, 0.07) |
| NC * IG | | | | 0.01 |
| | | | | (-0.07, 0.09) |
| Constant | $0.32^{***}$ | $0.24^{***}$ | $0.32^{***}$ | $0.24^{***}$ |
| | (0.30, 0.35) | (0.21, 0.27) | (0.29, 0.35) | (0.20, 0.28) |
| Observations | 538 | 538 | 538 | 538 |
| Log Likelihood | -81.75 | -50.27 | -81.72 | -50.18 |
| Akaike Inf. Crit. | 169.49 | 108.53 | 171.43 | 112.36 |

*Note:* $^{**}p < .05$, $^{***}p < .01$. NC=Number of cues, IG=Implied goal.

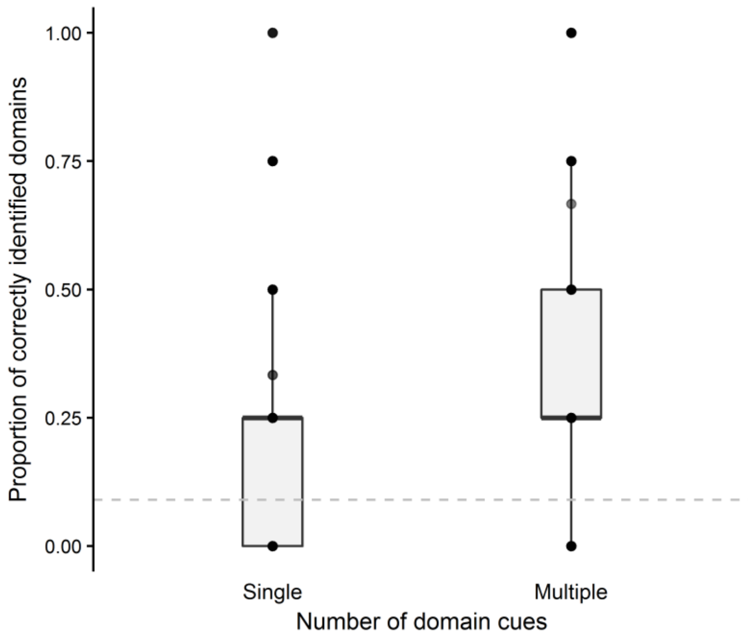


*Figure 3.* Accuracy of domain identification as a function of number of domain cues.

As can be seen in Figure 3, participants were significantly better than chance at recognizing the domains of actors with a single cue (24% of successful identification, 95%CI [0.21,0.27], $p < .0001$) and better yet for actors with multiple cues (40% of successful identification (95%CI [0.37,0.43]), $p < .0001$).

As with the first dependent variable, we saw that when participants were merely instructed to browse through a timeline of social media posts, they spontaneously inferred actors' domains of expertise from their posts (H3), but only for actors who had multiple expertise-implying posts (H4).

Informing participants about an upcoming expertise-related task, which could be expected to make expertise more salient and/or set an implicit goal to monitor expertise (H5), did not seem to affect the extent to which participants made inferences. An important conclusion here was that domain inferences to occurred even when there when there was no particular salience of expertise (H3). It is not entirely clear why the implicit goal had no effect. One explanation would be that inferences were made regardless of topic salience. This would be in line with the idea of spontaneity. However, since many participants failed the manipulation check, an alternative explanation could be that the manipulation was unsuccessful. In attempt to rule out this explanation, we did a set of exploratory analyses, where we repeated our primary analyses on a subset of participants who passed the manipulation check. Again, the implied goal factor did not improve model fit over number of cues ($\chi^2 = 111.32$ , $p < .0001$). That is, the results were analogous to the initial analyses, which suggests that the first explanation offered above, that our manipulation was not successful, is unlikely.

**Impressions.** We used forced-choice trials to compare whether our manipulations of domain expertise (neutral vs. domain related posts) and exposure (number of cues) influenced participants impressions of the actors' approachability and competence. On each trial participants were asked to make a choice between two faces belonging to different groups. This resulted in four trials per comparison. We considered all trials and ran binomial tests to determine whether one of the two groups in each comparison was chosen more often.

Results can be seen in Figure 4. As predicted, actors with domain-implied posts who were seen more often (with multiple neutral cues) were more likely to be chosen as approachable, compared to actors who were seen once (single neutral cue; $p = 0.0006$). This was also the case for domain cues ($p = 0.0004$). The effect of exposure was independent of post type: Actors with multiple neutral and domain-related cues were chosen equally often ($p = 0.8789$). This pattern is in line with the idea of a mere exposure effect.

With regard to competence, multiple exposure did not influence judgments when the cues were domain-irrelevant ($p = 0.1899$). Exposure to domain-related cues did influence judgments.

Participants were more likely to select actors with multiple domain-related cues as more competent than actors with a single domain-related ($p < .0001$) or multiple neutral cues ($p < .0001$).

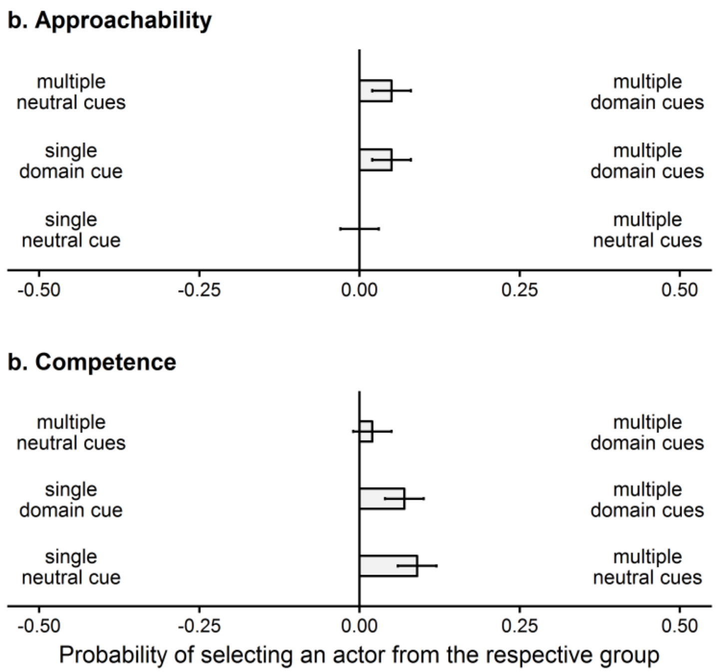


*Figure 4.* Probability of selecting an actor as more (a) approachable or (b) competent as a function of cue type (domain vs. neutral) and number (one vs. four cues).

Overall, the results from our impression formation measure reveals impressions consistent with mere exposure and spontaneous domain inferences. The effects are very small, which was to be expected, because we used a conservative measure. Dichotomous choice allows for very little variance. Furthermore, we had randomized highly influential factors, such as faces, and position (left versus right).

**Exploratory analyses.** While participants browsed the posts, they saw a 'Like' button on each post and were able to click it if they considered the post interesting. We also recorded the time they spent browsing and asked them for their own domains of interest. In our sample, the three were not substantially correlated (*r*s < .12).We examined how these factors relate to participants’ domain inferences, using the domain identification measure. To get a more complete picture, we plotted the effects separately for the number of cues factor, which we had previously found to influence domain inferences. The experiment was not specifically designed to test the effects of these factors, which is why we report no inferential statistics and only describe the data (Figure 5).

The analyses were performed on the level of single trials ($n$ = 4304). Proportion of correct instances of domain identification were computed separately for: trials in which there was a match between an actor’s implied domain and the observers’ self-reported interests and trials in which there was no match (Figure 5a); trials where observers had ‘Liked’ one of actors’ posts and trials in which they did not (Figure 5b); trials from observers whose browsing time was below the median and trials from observers’ whose time was over the median (Figure5c).

Overall, all factors increased the participants' likelihood to spontaneously infer actors' domains of interest while browsing. Again, inferences for frequently seen actors (multiple cues) were more pronounced and that was especially the case when participants saw actors whose domains of expertise matched their own interest, whose posts they liked, and when they spent longer time browsing. Our previous analyses revealed that domain inferences were stronger when participants saw multiple domain-implying cues. An interesting insight from the exploratory analyses is that if an actor's domain matched participants own interests or if participants browsed longer, they were more likely to infer actors' expertise even from single cues.

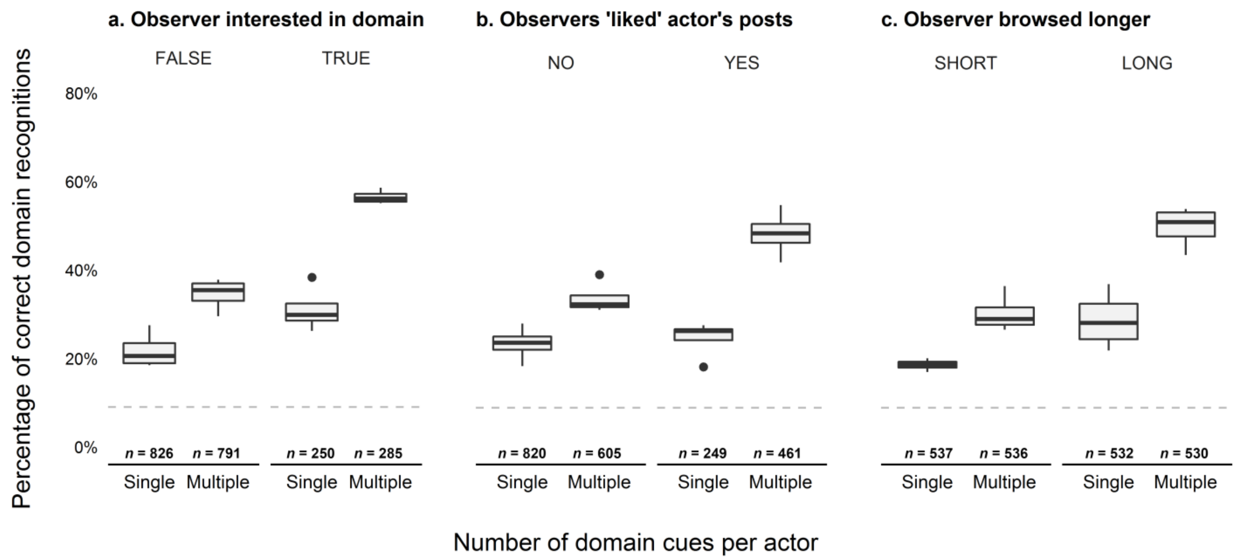


*Figure 5.* Exploratory analyses on domain recognition as a function of number of cues and (a) matching domain, (b) liking of posts, and (c) browsing time.

## General Discussion

We began by asking whether and how people manage to keep up with their large but increasingly complex networks. Our findings suggest that amid the all too frequent activity of browsing social media posts, people spontaneously, without deliberate effort or intention, extract information about who knows what. Brief glances at posts such "Front-end developer aka JavaScript wizard, hire me!" were sufficient for participants to infer the implied domain ("programming") and associate it with the person who posted the update. We used an indirect measure, which was based on false recognitions (i.e., mistakes), thus ruling out the possibility that the effect was due to memorizing the materials. The conditions under which we observed the effect closely resembled casual social media browsing. This leads us to expect that processes of spontaneously domain recognition occur in everyday life.

Contemporary information technologies and the unprecedentedly large networks they help us build and maintain make the promise of "social supernets" (Donath, 2007), but we have little understanding of how their potential is realized and how it can be enhanced. Ambient awareness -- the idea that people process and make sense of the overwhelming influx of social information efficiently -- has so far received limited support. By showing that the spontaneous trait inference effect extends to domains of expertise in a social-media environment, we provide a foundation for explicating the construct and its implications for online social networks.

Spontaneous trait inference is an astounding social process, with broad implications for human social cognition. The theoretical antecedents of the phenomenon are still actively debated (Moskowitz & Olcaysoy Okten, 2016). Our finding that people infer domains of expertise from short descriptions of behavior as readily and efficiently as they infer traits and values, adds to the body of work on spontaneous inferences (Uleman et al., 2008) and builds towards its conceptual understanding.

Our current conceptualization of expertise was in terms of domains rather than degree of competence. This conceptualization is close to the notion of knowing who knows what in order to find potential sources of information or referrals, and therefore of primary interest to us. Competence is critical for particular aspects of the information exchange process (e.g., judging the credibility of received information) and for other tasks such as expert selection. It demands further investigation. Future research could consider the digital footprints of high and low competence (e.g., linguistic markers, endorsements) and whether people can reliably identify them, either spontaneously or deliberately.

We demonstrated the mechanism through which social media users can develop expertise awareness. The extent to which they actually do so, would depend on the content to which they are exposed. Our experiments featured plausible social-media-like domain cues, but we do not know how common it is for people to post such information. Automated analyses, which identify domain-relevant content on a large scale, would be an interesting means of exploring this question. Another direction for further research would be to examine cues of different warranting value (informativeness, credibility) and how they affect judgments.

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# Appendix E

EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN

**Mathematisch-**
**Naturwissenschaftliche**
**Fakultät**

**Erklärung nach § 5 Abs. 2 Nr. 8 der Promotionsordnung der Math.-Nat. Fakultät**
**-Anteil an gemeinschaftlichen Veröffentlichungen-**
**<u>Nur bei kumulativer Dissertation erforderlich</u>!**

**Declaration according to § 5 Abs. 2 No. 8 of the PromO of the Faculty of Science**
**-Share in publications done in team work-**

Name:

**List of Publications**

1. Levordashka, A., & Utz, S. (2016). Ambient awareness: From random noise to digital closeness in online social networks. *Computers in Human Behavior, 60*, 147–154. http://doi.org/10.1016/j.chb.2016.02.037
2. Levordashka, A., & Utz, S. (2016). Spontaneous trait inferences on social media. *Social Psychological and Personality Science, 8*, 93–101. http://doi.org/10.1177/1948550616663803
3. Levordashka, A., & Utz, S. (Submitted). Ambient awareness of who knows what: Spontaneous inferences of domain expertise.

| **Nr.** | **Accepted for publication yes/no** | **Number of all authors** | Position of the candidate in list of authors | Scientific ideas of candidate (%) | Data generation by candidate (%) | Analysis and Interpretation by candidate (%) | Paper writing by candidate (%) |
|---|---|---|---|---|---|---|---|
| | | | *Optional, the declaration of the own share can also be done in words, please add an extra sheet.* | | | | |
| **1** | Yes | 2 | 1 | 80 | 80 | 80 | 90 |
| **2** | Yes | 2 | 1 | 80 | 90 | 90 | 90 |
| **3** | No | 2 | 1 | 50 | 90 | 90 | 90 |

I certify that the above statement is correct.

Date, Signature of the candidate

I/We certify that the above statement is correct.

Date, Signature of the doctoral committee or at least of one of the supervisors

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## Education

**Ph.D. in Psychology, summa cum laude, Eberhard Karls University of Tübingen. Nov. 2013 – July 2017.**
Thesis: "Spontaneous inferences on social media and their implication for ambient awareness"

**M.Sc. in Social Psychology (Research Master), VU University Amsterdam. Sept. 2011 – Aug. 2013.**
Thesis: "Effects of Questionnaire Design on Respondent Experience and Data Quality"

**B.A. in Social & Cognitive Psychology, Jacobs University Bremen. Sept. 2008 – May 2011.**
Thesis: "Paralinguistic text-based mimicry in computer-mediated communication"

## Academic Experience

**Researcher, Leibniz-Institut für Wissensmedien, Germany. Since Nov. 2013.**
Conducting research within the ERC project of Prof. Sonja Utz "Redefining Tie Strength (ReDefTie): How social media (can) help us get non-redundant useful information and emotional support."

**Visiting researcher, University of Bath School of Management, UK. April – May 2017.**
Visiting the group of Prof. Adam Joinson. Developing and conducting research on the effect of fact-checking feedback on online news sharing.

**Research Assistant, Network Institute, VU University Amsterdam. Oct. 2012 – Aug. 2013.**
Designing, conducting, and analyzing experiments within a transdisciplinary project.
The experiments were programmed as interactive web-based environments (JavaScript and PHP).

**Independent research project, VU University Amsterdam. Fall 2012–Summer 2013.**
Creating "Ostracism Online": A social-media inspired paradigm for experimental research on ostracism and social exclusion. Supervised by Prof. Kip Williams.

**Research Assistant (intern), Dr. Ashton-James, VU University Amsterdam. Summer 2012.**
Preparation of publication manuscript on the mimicry behaviour of people with narcissistic personality.

**Research Assistant (intern), Affective Neuroscience Lab, University of Konstanz. Summer 2010.**
Designing and pretesting an EEG experiment on the emotional memory of faces.

## Teaching Experience

**Co-teacher with Dr. Emese Domahidi, University of Mannheim. Spring 2017.**
Course: *Introduction to Data Analysis Using R*

**Co-teacher with Dr. Florian Landkammer, University of Tübingen. Spring 2016.**
Course: *Empirical Seminar on Knowledge Exchange and Trust within Organizations*

**Teaching Assistant of Dr. Özen Odag, Jacobs University Bremen. Fall 2010, Spring 2011.**
Courses:*Qualitative Research: Methods & Methodology* (MA); *Qualitative Research Methods* (BA)

**Teaching Assistant of Dr. Song Yan, Jacobs University Bremen. Fall 2009, Fall 2010.**
Course: *Laboratory Course in Experimental Psychology I*

## Publications

**Levordashka, A.**, & Utz, S. (2017). Spontaneous trait inferences on social media. *Social Psychological and Personality Science, 8*, 93-101. doi:10.1177/1948550616663803

Utz, S. & **Levordashka, A.**,(2017). Knowledge networks in social media. In S. Schwan & U. Cress (Eds.), *The Psychology of Digital Learning*. Springer. doi:10.1007/978-3-319-49077-9_9

**Levordashka, A.**, Utz, S., & Ambros, R. (2016, March). What's in a Like? Motivations for Pressing the Like Button. In 10th International AAAI Conference on Web and Social Media.

Lin, R., **Levordashka, A.**, & Utz, S. (2016). Ambient intimacy on Twitter. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 10*, article 6. doi:10.5817/CP2016-1-6

**Levordashka, A.**, & Utz, S. (2016). Ambient awareness: From random noise to digital closeness in online social networks. *Computers in Human Behavior, 60*, 147-154. doi:10.1016/j.chb.2016.02.037

Wolf, W., **Levordashka, A.**, Ruff, J. R., Kraaijeveld, S., Lueckmann, J. M., & Williams, K. D. (2014). Ostracism online: A social media ostracism paradigm. *Behavior Research Methods, 47*, 361-373. doi:10.3758/s13428-014-0475-x.

Ashton-James, C. E., & **Levordashka, A.** (2013). When the wolf wears sheep's clothing: Individual differences in the desire to be liked influence non-conscious behavioral mimicry. *Social Psychological and Personality Science, 4* 643-648. doi:10.1177/1948550613476097

## Peer-reviewed conference contributions

**Levordashka, A.** & Utz, S. (2017, July). Spontaneous inferences of domain expertise. Poster presented at the *18th General Meeting of EASP*, Granada, Spain.

Domahidi, E., **Levordashka, A.** & Frazen, V. (2017, July). Work related social support in Q&A sites: A content analysis approach. Poster presented at the *International Conference on Computational Social Science (IC2S2)*, Cologne, Germany.

**Levordashka, A.** & Utz, S. (2017, May). The Signal in the Noise: Browsing Social Media Augments Users' Awareness of Who Knows What. Poster presented at the *29th Annual Convention of APS*, Boston, USA.

**Levordashka, A.** & Lückmann, J. (2016, September). Ostracism Online paradigm revisited: Extended features and their implications for future research. In Schade, H. M. (Chair), Social Exclusion (Part II): Paradigms and Consequences. Symposium conducted at the 50th conference of the German Psychological Society (DGPs), Leipzig, Germany.

**Levordashka, A.**, Utz, S. & Lin, R. (2016, June). I read your updates, I read you: Spontaneous trait inferences on social media. Paper presented at the *66th Annual ICA Conference*, Fukuoka, Japan

**Levordashka, A.**, Muscanell, N. & Utz, S. (2016, February). Snap judgments on social media: What we infer from 140 characters or less. Poster presented at the *Annual Convention of the Society for Personality and Social Psychology (SPSP)*, San Diego, CA.

**Levordashka, A.** & Utz, S. (2015, September). Spontaneous trait inferences on social media. Talk at the *9th Conference of the Media Psychology Division*, Tübingen, Germany.

**Levordashka, A.** (2015, July). Ambient awareness: Can browsing provide awareness of online networks. Poster presented at *Living with Media International Summer School*, Cologne, Germany.

**Levordashka, A.** Lin, R., & Utz, S. (2015, May). Ambient awareness: Interpersonal knowledge in social media. Paper presented at the *65th Annual ICA Conference*, San Juan, Puerto Rico.

**Levordashka, A.** & Wolf, W. (2015, July). Ostracism online: A social media ostracism paradigm. Poster presented at *17th General Meeting of EASP*, Amsterdam, Netherlands.

## Practical Courses & Workshops

**Introduction to Data Science with Python**. GESIS Methods Seminar. Cologne, July 2017.

**Crowdsourcing Research: Transcending Disciplinary Boundaries**. Dagstuhl meeting. August 2016.

**EASP Summer School in Social Psychology**. Exeter, August 2016.

**International Summer School Living With Media.** Cologne, August 2015.

## Awards & Scholarships

**Top student paper** of the Communication & Technology division of ICA. Fukuoka, June 2016.

**Top poster award**, International Summer School Living with Media, Cologne, July 2015.

**VU Fellowship Programme Scholarship (VUFP)**, VU University. Academic year 2012/2013.

**William James Scholarship** by William James Graduate School, VU University. Academic year 2011/2012.

## Computer Skills

**Research.** R, SPSS, PsychoPy, Eprime, SuperLab, Authorware, CMA, Qualtrics.

**Programming (basic skills).** JavaScript, HTML/CSS, JSON, Twitter API, R Shiny.

**Graphics & desktop publishing.** Adobe CS (Photoshop, Illustrator, InDesign), Corel DRAW.

**Office & typesetting.** MS Office (Word, Powerpoint, Excel), Open Office, LaTeX.