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Improving Personality Judgement Accuracy Through the Training of Relevant Cues on Instagram and Twitter

by

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Idaho State University

A dissertation

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Committee Approval

To the Graduate Faculty:

The members of the committee appointed to examine the dissertation of Chloe San Miguel find it satisfactory and recommend that it be accepted.

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RE: Study Number IRB-FY2023-218 : Training Personality Judgement Accuracy on Twitter

Dear Ms. Pedersen:

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(208-282-2179; email humsubj@isu.edu)
if you have any questions or require further information.

Sincerely,

Ralph Baergen, PhD, MPH, CIP
Human Subjects Chair

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Improving Personality Judgement Accuracy Through the Training of Relevant Cues on Instagram and Twitter

Dissertation Abstract—Idaho State University (2023)

With the increasing prevalence of social networking sites (SNS), understanding how individuals perceive and judge each other in online contexts is vital. This dissertation investigates the accuracy of personality judgements made based on two popular platforms, Twitter and Instagram. This dissertation builds upon previous research which found Instagram profiles provided for more accurate personality judgements, explores the cues that contribute to accurate perceptions in these online spaces, and evaluates two methods of training individuals to improve personality judgement accuracy based on Twitter profiles. In Study 1, cues were coded on 102 social media profiles, with coders recording a variety of objective and subjective cues both common across platforms and unique to each platform. The Brunswick Lens Model was utilized to identify cues that were valid (actually pertaining to the targets'/profile owners' personality) and/or utilized (used by judges to form impressions). The hypothesis that higher levels of anonymity on Twitter would explain differences in accuracy between platforms was also assessed. Anonymity was not found to differ significantly between platforms, but was found to influence normative perceptions, with less anonymous targets being perceived with higher normativity. Study 2 evaluated two methods for training and improving judgement accuracy based on Twitter profiles. Utilizing valid yet unutilized cues identified in Study 1, 100 judges received online training about the personality traits of open-mindedness and conscientiousness, and cues on Twitter profiles that are indicative of those traits. Half of these 100 judges also received personalized feedback about the accuracy of their judgements. Fifty judges served as a control group and received no training. It was predicted that judges that received training and feedback would be more accurate than judges that received only training, and that both training groups would be more accurate in their perceptions than the control group. Training was not found to significantly improve judgement accuracy, but valuable insights and avenues for future research were uncovered. This research contributes to the understanding of both the complexities of social relationships online and research on training and improving judgement accuracy.

Keywords: personality, social media, personality impressions, personality judgement accuracy, social networking, training accuracy, improving accuracy

Chapter 1: Introduction

As of 2022, 72% of adults in the United States use social networking sites (SNS; Pew Research Center, 2022) with most global estimates around 58%, and nine out of ten internet users using social platforms (Hootsuite, 2022; Statista, 2021). Amplified by the COVID-19 pandemic, aspects of daily life that were previously performed in face-to-face (FtF) contexts have shifted partially or entirely into online spaces. As more and more of individuals lives take place within the context of online social platforms, from meeting life partners on apps like Tinder or Bumble to finding job opportunities on LinkedIn and then interviewing via Zoom, the nuances of how people present themselves and interact with others in online spaces prompts many questions of increasing importance. Among these are questions of first impressions and interpersonal judgements. *How do others perceive me based on my online presence? Are they judging me accurately? What information are they using to come to their conclusions? Am I judging others online as they really are? How can I get better at making accurate judgements?*

Individuals form and update impressions of the personalities of other people and often rely on these judgements to guide how they behave with others and handle social relationships. Within the context of an in-person, or face-to-face (FtF), interaction, there are many channels of communication, including verbal and nonverbal behaviors, that help us build impressions and judgements of others. The process of FtF interactions involves visual cues such as facial expressions, eye gaze and movement, posture, head and body movements, and hand gestures. Other, more static nonverbal cues include gender expression, race, dress, hairstyle/facial hair, and grooming (Burroughs et al., 1991; Gosling & Standen, 1998; Riggio & Riggio, 2012). Auditory nonverbal cues of tone, pitch, pace, volume, and other vocal qualities also convey information in FtF interactions. However, these cues are lacking, or drastically altered in form, in the majority of online contexts. While some might expect online contexts to thus result in less accurate perceptions, some research of online contexts suggests that certain qualities may actually be easier to perceive accurately. For example, although the trait of openness to experience is often difficult to judge accurately in FtF interactions, using emails as judgement stimuli has been shown to allow for comparatively accurate judgements of openness (Markey & Wells, 2002; Vazire & Gosling, 2004). Studies on Facebook have found significant levels of judgement accuracy for all of the Big Five traits, with patterns similar to FtF contexts (Back et al., 2010; Gosling et al., 2007). For example, in FtF interactions, extraversion is often judged with the highest levels of accuracy, and neuroticism with the lowest accuracy, and this pattern was replicated in judgements based on Facebook profiles (Back et al., 2010). So, while accurate impressions can certainly be formed via SNS, what is less clear is what cues are specifically being used to form these impressions.

Additionally, social media is not a singular context, but many unique contexts that exist across the wide variety of popular platforms, with the most obvious differences originating from the type of content a platform was designed to host. For example, Instagram is primarily a photo-sharing app, while Twitter is primarily used for sharing brief snippets of written text. These fundamental differences in content may lead to differences in personality judgement accuracy. Judgements made based on Twitter profiles have been found to be more accurate for traits that are considered to be typically less visible, such as neuroticism and agreeableness, compared to other traits (Qiu et al., 2012). This suggests that something about the specific context of Twitter as an online space increases the availability of certain cues relevant to these traits; cues that are not necessarily present in other contexts.

The present study builds upon my thesis, which investigated the extent to which accurate judgements of personality, political ideology, and political party affiliation can be made using only Twitter or Instagram profiles as stimuli (Pedersen, 2020). It was found that while both platforms appear to provide enough information for judges to form accurate personality judgements, Instagram provided for significantly more accurate judgements than Twitter. Differences between platforms were found to be more complex when traits were examined individually, with Instagram providing for distinctively accurate judgements of extraversion, open-mindedness, and agreeableness, while Twitter provided for distinctively accurate judgements of negative emotionality and agreeableness. These differences in accuracy are likely due to the presence of different cues within the unique context provided by each platform.

The present study has two goals. First and foremost, this study identifies a number of the specific personality-relevant cues that are present within Instagram and Twitter profiles, including cues found across platforms and cues unique to each platform, and identifies how these cues relate to more or less accurate personality judgements. Second, this study aims to test two methods of training individuals about how specific cues on SNSs relate to personality traits to see which method, if either, most improves personality judgement accuracy on social media profiles.

Chapter 2: Study 1 Literature Review

Understanding our perceptions of others, others' judgements of us, and the extent to which these judgements are accurate, is important in all social and interpersonal contexts. Beginning with first impressions, individuals use judgements of the personalities of others to help explain their behavior and to predict how they would act in potential future situations. These judgements and predictions influence behavior towards others, and subsequent relationships. Some people tend to be more accurate in their judgements of others, and some people tend to be judged more accurately by others. These two sorts of people are referred to as the *good judge* and the *good target*, respectively. Being a good judge or good target is related to numerous inter- and intrapersonal benefits (Coleman, 2021; Letzring, 2008, 2015). Aspects of intelligence such as emotional and dispositional intelligence, attention, memory, and social skills have all been found to be prevalent in good judges (Allport, 1937; Christiansen et al., 2005; De Kock et al., 2015; Taft, 1955; Vernon, 1933). Additionally, it makes sense that good judges of personality find themselves facing the negative consequences of inaccuracy more rarely.

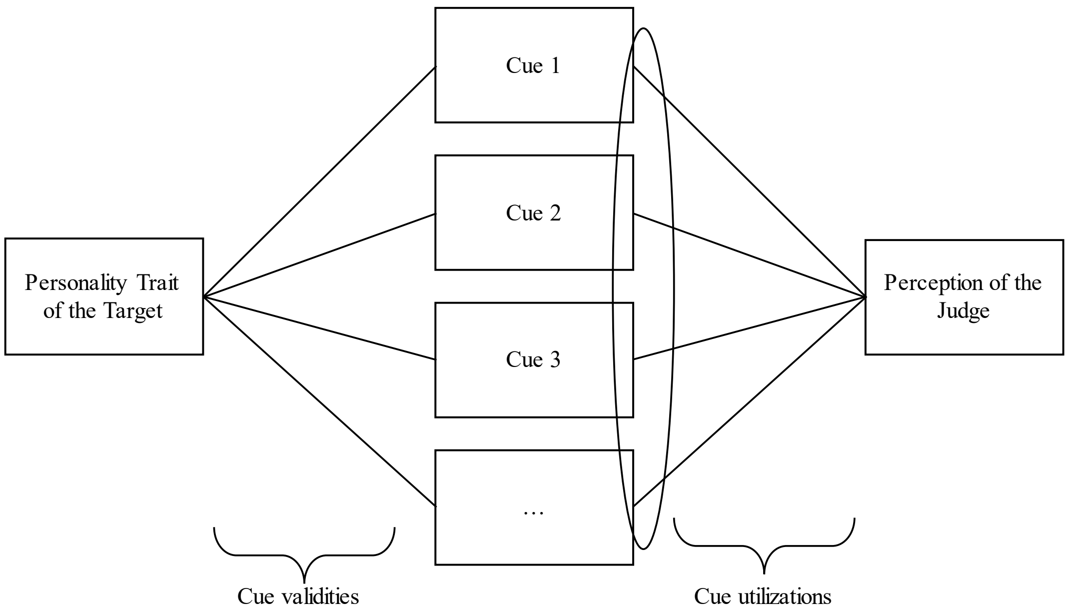
There are a few theoretical models that are important to consider when understanding how cues are used to form accurate personality judgements. Specifically, I focus on Brunswik's Lens Model (1956) and the Realistic Accuracy Model, or RAM (Funder, 1995), which is based on Brunswik's Lens Model. Two of the four moderators of RAM are of particular interest within this study: the good trait and good information. Additionally, how these aspects relate to models of computer-mediated communication, anonymity, and past research on impression-formation in online contexts are be explored. Of specific interest is past research on Instagram and Twitter, including the findings of my thesis, on which the current study builds. Finally, research on the training and improving of judgement accuracy is discussed.

Brunswik's Lens Model

Brunswik's Lens Model (1956) was developed to provide a way to think about and describe the relationship between the environment and the behavior of organisms. Adapting this model to specifically examine interpersonal judgements, judges or perceivers use whatever is available within the environment or situation (i.e., cues) to judge the personality of the target, which is not directly observable. These observable cues are the "lens" through which judges are perceiving the underlying personality of the targets. The incorporation of a cue into a judgement is called *cue utilization*, and the extent to which a cue is actually related to the aspect or trait being judged is called *cue validity.* Figure 1 illustrates the components of this model. Accurate judgements thus occur when the cues that are utilized by the judge are also the cues that are valid. The more judges rely on valid cues rather than invalid ones, the more accurate they will be in their perceptions. An important note about Brunswik's Lens Model is that this model not only provides a simple description of the process of judgement, but can also be used to compute the validity and utilization of each cue.

Figure 1

Brunswik's Lens Model



Measuring Personality

In order to compute this information, a realistic criterion for the actual personality of the target must be obtained. This idea is not without its nuances and controversies. Beginning as early as the 1940s and brought into the spotlight in 1968 by Walter Mischel's critique, the "person-situation debate" refers to the debate of whether individual differences or the external situation is more influential in determining a person's behavior. There are many aspects of psychology as a field that operate on the assumption that personality is relatively consistent and influences behavior. From clinicians using standard assessments, to industrial organizational psychologists designing personnel selection methods, it is assumed that there are individual differences among people that are somewhat consistent across situations, and that have ramifications for their thoughts, feelings, and behaviors. One "solution" to the person-situation debate is synthesis, as suggested by Fleeson and Noftle (2009). For this synthetic solution, the idea of cross-situational behavioral consistency needs to be reconsidered. Cross-situational correlations for specific behaviors are often low, however, aggregates of behavior are more consistent. Additionally, the amount of consistency across traits is variable, and this consistency can represent the strength or importance of each underlying trait. More important traits assert a greater influence over behavior, resulting in greater consistency. A related conception is the Density Distributions approach. Fleeson (2001) proposed that traits are best conceptualized as distributions of behaviors and states, with individuals acting in-line with their underlying personality traits the majority of the time, resulting in a high consistency of the mean of behavior, while allowing for consistency of single behaviors to be low and responsive to situational variables.

Personality is frequently measured with self-ratings on some personality measure, such as the Big Five Inventory. But how can researchers be sure that an individual is accurate about their self-judgements? This approach has distinct limitations relating to the biases and introspective ability of the targets. For self-reports to be accurate, individuals must be able to honestly and objectively evaluate their own personality. One approach to mitigating this issue is referred to as a realistic approach (Funder, 1995), which is based on the process of construct validation (Campbell & Fiske, 1959; Cronbach & Meehl, 1955). The idea is that if an assessment of personality (or personality judgment) is accurate, it should agree with other measures of the same construct. Inclusion of *acquaintance-reports*, or reports of personality provided by other individuals close to the target, in the accuracy criteria is generally preferred to help mitigate the limitations of self-reporting (Funder, 2012). Generally, the closer the relationship, the more self-ratings and acquaintance-ratings tend to match up (Connelly & Ones, 2010). The longer the relationship between the judge and target, the more accurate the judgements tend to be, which is known as the *acquaintanceship effect* (Biesanz et al., 2007; Colvin & Funder, 1991). The amount of agreement between one's self-ratings and the ratings of another individual is also termed *self-other agreement* and meta-analytic results show that self-other agreement among family, friends, and cohabitators is higher than that among strangers, acquaintances, and work colleagues, although there is still evidence for self-other agreement among these more distant social relationships. Meta-analyses have found self-other agreement for the Big Five personality traits to range from .40 (Vazire & Carlson, 2010) to .55 (Connolly et al., 2007). By combining self-ratings with ratings provided by peers or acquaintances, researchers are able to more accurately represent the target's true personality (Funder, 1995; Letzring et al., 2006; Letzring & Human, 2014). This composite score is often referred to as the *realistic accuracy criterion*, and when judgements are compared to this criterion, the level of agreement is referred to as *realistic accuracy*.

Although the gold standard in personality judgement accuracy involves building an accuracy criterion using acquaintance-reports from individuals who know the target well, self-other agreement is also commonly used. The differences in predictive validity between self-report and acquaintance-reports are not large (Kolar et al., 1996) and meta-analytic results indicate that self-report means of the Big Five generally do not differ from informant-report means, except in cases in which the informant is a stranger (Kim et al., 2018). Importantly for this project, utilizing self-other agreement as the accuracy criterion reduces barriers to collecting qualified target participants. In situations where the study design leads to other target eligibility requirements (such as high levels of social media usage on a specific site), removing the requirement of acquaintance-reports often results in more timely data collection.

Components of Accuracy

Personality judgement accuracy can be broken down conceptually into components of accuracy. Consider a situation in which an individual target is perceived very accurately by a judge. It is possible that the judge is high in *perceptive accuracy*, or the extent to which a particular judge's impressions are more or less accurate compared to other judges across different targets. An individual high in perceptive accuracy may also be described as a good judge. On the other hand, the high level of accuracy could be attributed to the target's *expressive accuracy*, or the extent to which a target is accurately judged on average by different judges. Individuals with high expressive accuracy are good targets (Biesanz, 2010).

It is also necessary to understand that researchers often divide accuracy into normativity and distinctive accuracy. *Normativity* represents the extent to which a target is accurately judged as being similar to others, while *distinctive accuracy* represents the extent to which a target is accurately judged as being unique from others (Biesanz, 2010). When forming perceptions of others, individuals often rely on information that is not directly connected to the target. One such source of information is the judge's perception of what the average person is like. The personality profile of the average person is called the *normative profile*. If judges rely heavily on the normative profile when judging most people, they will usually be at least somewhat accurate, because by definition, most people are similar to the average person. However, once an individual's personality profile has had the normative profile removed, what remains is the *distinctive profile*. The distinctive aspects of an individual's personality, what makes them unique and different, is often what people are most interested in when forming perceptions of others. However, if you simply ignore the normative aspects of an individual, you would likely be ignoring a large portion of their personality. By examining both of these components, a richer understanding of judgement accuracy is possible.

The Realistic Accuracy Model

The Realistic Accuracy Model (RAM) proposes that personality judgment is a four-step process. These four steps are relevance, availability, detection, and utilization. First, the target must exhibit a cue that is relevant to an aspect of personality. Next, the target must make that cue available, or externalized, so that it may be detected by the judge. In order to detect a cue, a judge must be paying attention to the target. Finally, the judge must correctly utilize that cue as being indicative of the relevant personality trait. For example, connecting the cue of talkativeness to the trait of extraversion will result in more accurate judgments because talkativeness is a valid cue for extraversion. All of these steps must occur in this order for an accurate judgement to be made.

There are many variables, or moderators, that can influence levels of accuracy. These variables can be organized into four categories: the good judge, the good target, good information, and the good trait (Funder, 1995). The good judge is one who is consistently highly accurate. In terms of RAM stages, good judges are more adept at detection and utilization. This ability is likely related to the aforementioned qualities of good judges (e.g., emotional/dispositional intelligence, attention, memory, social skills). Additionally, in interactive situations, these social skills may help the target feel more comfortable, and thus the good judge can also influence the relevance and availability stages. The good target is someone who is consistently judged more accurately. In general, good targets tend to be more psychologically well-adjusted, have higher social status, and are in more social roles or contexts that promote expressivity (Human & Biesanz, 2013). Good information and the good trait are both of particular relevance to the proposed study.

The Good Trait

Personality traits and characteristics differ in how accurately they tend to be judged. The good trait is a trait that is judged with relatively high accuracy across situations. Good traits provide a higher number of relevant cues that are observable, or visible, in a wide variety of situations (Krzyzaniak & Letzring, 2021). For example, extraversion is often considered a good trait because there are many outward behavioral cues that are somewhat definitionally related to extraversion (e.g., sociability, talkativeness). Compare this to neuroticism, which is characterized by thoughts and feelings that are largely internal (e.g., anxiety, worry) and thus provide less easily observable cues in most contexts. However, in socially stressful situations, judgements for the trait of neuroticism have been found to be more accurate (Hirschmüller et al., 2015), which exemplifies the importance of the situation's relevance to the trait in question. In terms of RAM, in most situations cues for neuroticism often do not meet the requirements of the second stage of the model: availability. If a cue is not made available, then a judge cannot detect or utilize it. In terms of Brunswik's Lens Model, cues such as worry or stress may be very valid (or, in RAM terms, relevant) to the trait of neuroticism, but they may not be utilized as frequently as more visible cues. However, for the purposes of the proposed study, it is important to consider that visibility of cues likely varies across social media platforms, as users are encouraged to express their thoughts, feelings, and other typically internal characteristics in addition to sharing behaviors that are performed both in public (e.g., social events, milestones, travel) and private (e.g., workouts, artistic expression, personal growth). Additionally, the social norms and expectations differ depending on the platform, as well as the cultural niche in which an individual user exists. For example, some sites seem to be fundamentally more politically oriented than others. On Twitter, political content is very common, with roughly a third of the content being political in nature and politicians making up a disproportionate number of the accounts followed (Pew Research, 2022). Of the top 50 most followed accounts on Twitter, 11 are political figures, government agencies, or news sites. However, of the top 50 most followed Instagram accounts, NASA is the only politically adjacent account as a federally funded space agency. Based on activity, the political tone on Twitter seems to be accepted and expected by users while in contrast, on Instagram and Facebook, Meta has continually adjusted algorithms to respond to feedback from users who want less political content in their feeds (Stepanov, 2021).

Good Information

There are two aspects of good information: quantity and quality. Regarding quantity, both longer observation of a recorded target and longer length of acquaintanceship with a target usually leads to more accurate judgements (Biesanz et al., 2007; Letzring et al., 2006). Meta-analytic research on acquaintanceship and accuracy (measured by self-other agreement) found that although increased frequency of interactions does improve accuracy, substantial increases in accuracy require interpersonal intimacy between the judge and the target (Connelly & Ones, 2010). Looking at acquaintances by category, family members consistently had the highest levels of accuracy when judging targets, followed by friends and cohabitators. Work colleagues and incidental acquaintances, which had high frequency of interactions but low levels of intimacy, had only small advantages in accuracy over strangers, who were generally the least accurate. Additionally, interpersonal intimacy was related to higher accuracy levels specifically for low-visibility traits, but only minimally related to accuracy in judging higher visibility traits. This aspect of interpersonal intimacy is likely also related to the quality of the information shared between individuals, with more intimate relationships being conducive for sharing more information related to traits of emotional stability and open-mindedness to experience. Considering that discussion of worries or negative emotions (cues to emotional stability/neuroticism) and musings about politics, religion, or other intellectual and philosophical topics (cues to openness to experience) with brand new acquaintances or coworkers would likely break the social norms surrounding such topics, it makes sense that this information would simply not be made available within certain relationships, even if information quantity is high.

Methods that manipulate the quantity of information while holding quality steady are easier to conceptualize and implement than the reverse. Conversations can be timed, videos edited in length, and social media profiles cropped to include more or less information. Experiments that are specifically interested in quality of information have to utilize more creative methods. Researchers have found that describing thoughts/feelings about a range of topics leads to more accurate judgements than describing behaviors surrounding those same topics (Andersen, 1984). Additionally, distinctive accuracy was higher when participants discussed thoughts, feelings, or behaviors, as opposed to engaging in behaviors together (Letzring & Human, 2014). The context of interactions also likely plays a role in information quality. Research examining the “richness” of three contexts (Internet chats, telephone, and FtF conversation) found greater accuracy for traits of neuroticism and extraversion in FtF interactions, followed by telephone chats, and the least accuracy based on Internet chats. The reverse pattern existed, however, for traits of openness and conscientiousness (Wall et al., 2013). The researchers interpreted these findings as indicating that “rich” contexts (where there are more verbal, paralinguistic, and nonverbal cues) are more conducive for judging extraversion and neuroticism, while more accurate judgements of conscientiousness and openness occur in “information-lean” contexts. However, as will be discussed later, it is possible that these results may also be explained by the unique qualities provided by computer mediated communication.

On a social media platform, someone with more frequent posts and/or lengthy written posts would provide a higher quantity of information. In a format like Twitter, however, quantity is somewhat standardized as all tweets must be less than 280 characters. Within the proposed study, the same number of posts are recorded for each target, and therefore information quantity is relatively consistent across targets. However, particularly observant judges may notice differences between targets in the frequency of posting, as dates and times of posts are shown. The quality of information on SNSs, while not being directly manipulated, is of central importance to this study. Examining the differences in cues between Instagram and Twitter profiles, as well as within each profile type, sheds more light on how the quality of information on social media relates to accurate judgements.

Impression Formation Online

By expanding outside the realm of accuracy and into impression formation more broadly, one can more fully understand how online contexts differ from FtF interactions, and how these differences may be influential to accuracy. While *impression formation* refers to the judge’s consideration of the target, *impression management* can be defined as how targets attempt to manage or control the perceptions others form of them (Bozeman & Kacmar, 1997; Drory & Zaidman, 2007). There has been much past research focusing on how FtF interactions and computer-mediated communications (CMC) differ from one another in terms of impression formation and management, beginning with the popularization of the social internet in the 1990s (e.g., Thompson & Fougler, 1996; Thompson & Filik, 2016; Walther & D’Addario, 2001). An important difference between FtF communication and CMC is the role of intentionality and the degree of control over impression management. While nonverbal cues in FtF interactions (e.g., facial expressions, gestures, movements) are mostly unintentional (Burgoon, 1994), there is greater control over what an individual presents or posts in online contexts. Thus, individuals play a more conscious role in impression management in online contexts.

It has been proposed that, relative to offline self-presentations, online presentations are more easily modified and editable, allowing for more selective versions of the self (Bargh et al., 2002; Ellison et al., 2006; Walther, 1996), and presentation of previously unexpressed aspects of identity (McKenna & Bargh, 1998). A factor ingrained in earlier studies of CMC and self-presentation online, however, was the relatively large amount of anonymity inherent on the internet before the rise of SNSs. Early iterations of online social platforms (e.g., blogs, chatrooms, personal websites) were largely disconnected from offline social circles in that the goal was typically to connect with people you did not know in-person. Even individuals with substantial online presences were not necessarily "Google-able" by offline acquaintances due to underdeveloped search engine optimization. Before Facebook was made available to the public, personality judgment accuracy research was applied to personal websites (Vazire & Gosling, 2004) and email addresses (Back et al., 2008), and found that these presentations typically represented accurate, although slightly enhanced (more similar to one's "ideal self"), personalities of their owners, when judged by close others (Vazire & Gosling, 2004). As sites like Facebook grew, and search engines became more sophisticated, the default amount of anonymity online decreased substantially. Now, many social applications will connect to Facebook, Gmail, or the contacts within your phone, such that you are often connected to the same networks of people by default. Creating a private, partially, or fully anonymized profile often takes more effort on the user's part. One common assumption is that online social networking profiles are used to create a version of an “idealized self” (Manago et al., 2008). However, the level of connection a profile has to the owner’s offline social network may serve as an indicator for the authenticity of the information presented. For example, it was found that the number of people aware of an individual’s online dating profile positively correlated with the accuracy of the profile photograph (Toma et al., 2008). Additionally, adolescents with fewer Facebook friends are more likely to present multiple versions of themselves online (Fullwood et al., 2016). Relatedly, misrepresenting oneself online where friends or family can see can have serious consequences. Judges consider misleading online information to be indicative of untrustworthiness and hypocrisy among both friends and acquaintances (DeAndrea & Walther, 2011).

Warranting theory (Walther & Parks, 2002) posits that judges are aware of this potential for inauthentic impression management and take it into account when forming impressions online. Due to the potential for inconsistencies between offline and online self-presentation, warranting theory posits that judges pay special attention on SNSs to cues that they perceive as valid for indicating someone’s offline characteristics. These cues are ones that are perceived as being less likely to be manipulated, such as information gained about someone through others in that person’s social network. Within the context of a SNS, things others say about a target or residual cues from online behavior may be considered more valid than things explicitly posted by the target themselves; these things have more warrant because they are not directly manipulated by the target (Walther & Parks, 2002; Walther, 2007). For example, if Person A posts a picture of Person B and “tags” them in it such that it appears on Person B’s page, it is less likely that Person B had control over how they appeared in the photograph than if they had taken and posted the photo themselves, perhaps even editing it prior to posting. Another example of behavior that might be considered as more valid is the residual evidence from online behavior that is typically less visible. For example, the Tweets that someone has "liked" can be viewed on a separate tab on their profile, but more novice users may not realize this. This has led to some notorious incidents wherein politicians or other public figures have received public backlash for liking inappropriate Tweets, not realizing these could be discovered by the public. Such situations, within the context of warranting theory, are considered more indicative of one's true behavior than more carefully curated social media posts.

Offline, it has been proposed that a high level of control over one's impressions is related to a number of positive outcomes. Well-adjusted individuals tend to be higher in impression management and self-presentation (Block, 1965; Uziel, 2010). Self-presentation often involves making both a positive first impression and an authentic one simultaneously. In offline contexts, it has been found that individuals are likely to provide relevant positive information over negative information, which facilitates accurate and positive judgements (Human et al., 2012). This is likely also true online, although the extent to which one can control their self-presentation online is also related to the specific online environment, as well as factors such as anonymity.

Anonymity on Social Networking Sites

In FtF interactions, a large number of visual cues (e.g., gender expression, race, clothing, makeup, hairstyle) can be used to make judgements, and also to assign social labels and stereotypes. These involuntary cues that come with being physically present mean that the degree of anonymity is typically low in these interactions. SNSs, however, provide for varying levels of anonymity. Anonymity in purely text-based sites can allow people to decide what personal factors they wish to reveal (Riordan & Kreuz, 2010). Perhaps surprisingly, spontaneous self-disclosure, unrelated to the task at hand, has been found to occur more frequently in CMC than in FtF interactions on the same topic (Joinson, 2001). This has been found to be beneficial to well-being in certain cases, as it can lead to greater freedom to express personal information (Amichai-Hamburger & Hayat, 2013; Joinson, 2001). This may even create more opportunities for individuals to be their “true selves” online (Bargh et al., 2002; also see the following section on Hyperpersonal Theory). This can be exemplified by the success of sites and apps that market themselves as places to reveal things anonymously, sometimes called anonymous-confession websites. These sites do not have typical social media “profiles” and contributions and posts are typically not tied to any username or account. The first widespread use of such websites can be found as early as 1999, with the introduction of 2channel, an anonymous Japanese textboard that was described as “Japan’s most popular online community” by 2007 (Sakamoto, 2011). The continued success of sites and apps like Whisper, This Website Will Self Destruct, and Ask.fm exemplify a desire, at least commercially, for anonymous-confession sites. Anonymity may allow individuals to safely investigate aspects of their identity that they would not otherwise feel comfortable with (Turkle, 1995). This safety in exploration may be particularly significant to members of marginalized communities, such as LGBTQ+ individuals, as they can express themselves without experiencing any social stigma in their offline lives, leading to greater self-esteem (Amichai-Hamburger & Hayat, 2013). However, the ramifications of this lowering of inhibitions due to anonymity are complex (Suler, 2004).

Anonymity can also be used in negative and destructive ways. The *online disinhibition effect* was coined to specifically refer to a willingness to do things online that would be considered inappropriate in person (Suler, 2004). This can be exemplified by controversies surrounding anonymous websites/apps, including popular but ultimately defunct anonymous sites and apps like Secret, YikYak (re-released in 2021 after being shut down in 2017), and After

School. Instances of cyberbullying and harassment, even to the point of associated suicides, have been recorded on such sites (e.g., Edwards, 2013; Shontell, 2015), as well as threats of bomb and gun violence (Safronova, 2017).

Anonymity is clearly an important aspect to consider when evaluating online personality cues. However, most SNSs, unlike the above examples, are not purely anonymous, but exist on an anonymity continuum (Qian & Scott, 2007). While some sites, such as Facebook, are designed to be used with an individual's real name and actual identifying information, many sites allow for the creation of usernames that may or may not reveal any identifying information. Some sites allow users to post using their username or anonymously, such as 4chan and Reddit. And even on sites that are designed with a specific level of anonymity for users in-mind, individuals can control their level of anonymity by the amount of identifying information they choose to share. Thus, SNSs have both objective aspects of anonymity (e.g., whether there is an option on the platform to have a profile photo) and subjective aspects (e.g., if that profile photo is a clear headshot, an animated avatar, or a photo of something entirely unrelated to the physical appearance of the user, and the level that an individual perceives themselves to be identifiable to others based on that photo). This level of subjective anonymity, and thus the sort of information shared, can vary greatly depending on the platform. For example, someone might feel safe revealing identifying information if other users of the platform are dispersed and unlikely to identify them offline (Fullwood, 2015). This can also be exemplified by the information that is shared as demographics of users shift. For example, as Facebook use has become more popular with older individuals, younger users have primarily migrated to other sites (Pew Research, 2021). Thus, users may experience feelings of increased anonymity simply because their offline friends or relatives are not present on a specific platform, regardless of the objective level of anonymity.

Additionally, beyond this anonymity continuum, there are internet users who intentionally adopt distinctly false names and identities online. The term "catfish," coined after the film and TV show of the same name, describes a person who uses images and/or identifying information of another person or persons to present themselves online (Attrill et al., 2015). This fabricated identity may be an exact replica of another person's profile or based on fake/stolen images and information from a variety of sources. A catfish may have one or more motivations in mind, from covert information gathering or stalking, to financial scamming, to inflicting psychological/emotional pain, to luring an individual into a position in which they can physically harm them (Lloyd et al., 2019). Catfishing is also a common tactic used by child-predators to groom and gain the trust of potential victims. Although this is a notable and dangerous aspect of anonymity online, there are also individuals who adopt an untrue persona online without malicious intent.

This can be shown in the relatively recent popularity of anonymous content creators such as VTubers (Virtual YouTubers) who use animated avatars to create content online, most often relating to videogames (Dodgson, 2021). These performers also may use stage names, voice changers, and stage personas, but are relatively transparent in their deceit and their main goal of entertainment. Individuals may also create social media profiles for fictional characters from popular media as a way to play-act the media that they enjoy. While many of these fan-fiction accounts may be considered harmless, there is always the potential for users to abuse their anonymity when interacting with others. "Parody" accounts, in which individuals pretend to be someone else for humor, commentary, or harassment, also exist in a liminal space between positive anonymity and negative anonymity. Thus, accounts that fall under the categories of catfish, anonymous content creator, fan-fiction, or parody, are not intended to portray the personality of the actual user. This poses problems for studies like the one at-hand that seek to explore the accuracy of personality judgements in an online context. Researchers, especially those interested in online personality, need to be aware of these social media trends and behaviors and carefully evaluate social media profiles before inclusion in studies.

Hyperpersonal Theory

The hyperpersonal model of communication arose in the 1990s and refers to heightened levels of intimacy and liking that have been observed in CMC, exceeding that of FtF communication (Walther, 1996). There are four components of CMC that, according to hyperpersonal theory, result in enhanced self-presentation and contribute to more favorable social outcomes. First, as discussed previously, social media users can exert more intentional control over how they present themselves online, with the ability to edit prior to posting/communicating. Second, CMC is asynchronous. Even in situations where instant responses are expected (e.g., Instant Messaging), individuals can take time to reflect on messages received and formulate responses without being observed or judged. Third, the lack of a shared physical space means that undesirable verbal and nonverbal communication cues, such as use of filler words (e.g., um, like), blushing, or shaking, can be hidden. Finally, cognitive resources that would go towards self-monitoring and interpreting nonverbal cues in FtF interactions are freed up and can be reallocated to focus on optimal self-presentation. Evidence in support of the hyperpersonal theory has been found specifically in individuals with lower self-esteem (Joinson, 2014) and in situations where negative social evaluations are more likely (Raveendhran, 2020). For example, adolescents who possess a less stable sense of self report a preference for socializing online, more regular experimentation with online self-presentation, and more frequently presenting an idealized version of the self (Fullwood et al., 2016).

Cues of Personality

As discussed in the previous section, individuals online can tactically manage impressions by being selective about the information they disclose, such as hobbies, interests, attitudes, and opinions. These sorts of cues, within one's direct control, have been termed *identity claims* (Gosling et al., 2005). However, there also exist unintentional cues via online behavior which others may use to form judgements, which are referred to as *behavioral residue*. These sorts of cues could include how language is used, information an individual is "tagged" in or otherwise included in that is shared by others, and information that individuals may be unaware is viewable, such as "liked" Tweets. Behavioral residue is conceptually similar to the cues that are more highly valued in Warranting Theory, in that this sort of information is likely less directly manipulated by the user for self-presentation purposes.

Reviewing past research on cue detection and utilization provides a starting point to consider which cues are likely to be used to make accurate judgements within a social media profile. The following sections pull largely from the excellent summary and meta-analytic work by Breil et al. (2021). Most of the cues discussed in the following sections are identified by Breil et al. (2021) as having at least small effects ($r > 0.10$) for both utilization and validity, in the same direction across at least two studies. When examining non-verbal cues specifically, past research has focused on the individual target themselves, based on a variety of stimuli such as video, photographs, and in-person interactions. However, when considering how this past research may relate to judgements made on social media, especially on the platforms of Instagram and Twitter, where users have complete control over the posts viewable on their pages, it is possible that the entire profile should be examined for these cues as opposed to only specifically the target themselves. For example, a picture of a person smiling, whether or not the person in the photo is the owner of the profile, could be a valid cue for the target's extraversion, as the target chose to post this specific image to their page. Additionally, research surrounding non-lexical cues of speech, also known as paralanguage, were identified by Breil et al. (2021). However, as these cues cannot be conveyed via written text, paralanguage cues are not coded in this study.

Extraversion

Beginning with extraversion, there are many nonverbal cues that can be present in FtF interactions as well as in photographs, such as a cheerful facial expression, and more specifically smiling. Friendly or positive facial expressions serve as valid cues for extraversion (Albright et al., 1997; Back et al., 2010; Borkenau & Liebler, 1992; Meier et al., 2010; Schultheiss & Brunstein, 2002). A dominant facial expression and more general facial expressiveness are also valid cues of extraversion (Berry & Hansen, 2000; Borkenau & Liebler, 1992, 1995; Hartung & Renner, 2011; Lippa, 1998; Petrican et al., 2014). The appearance of a target, including broader cues such as attractiveness, neatness, and stylishness, as well as more specific cues such as not having eyeglasses, a larger mouth/fuller lips, longer hair, and not wearing dark clothes have also been found to be both valid and utilized cues for judging extraversion (Borkenau & Liebler, 1992, 1995; Hartung & Renner, 2011; Kenny et al., 1992; Meier et al., 2010; Nauman et al., 2009; Nestler et al., 2012; Stopfer et al., 2014; Vazire et al., 2008). Body language, including a forward lean, use of more gestures, self-assured posture and less apparent tension/nervousness, are also cues of a more extraverted person, although it is unlikely that these cues will be present on SNSs (Back et al., 2010; Borkenau & Liebler, 1992, 1995; Hartung & Renner, 2011;

Levesque & Kenny, 1993; Lippa, 1998; Naumann et al., 2009; Simpson et al., 1993). Similarly, a number of paralanguage cues are also indicative of extraversion (e.g., expressive/varying voice, pleasantness of voice, loudness, speech rate).

The words that are used in an interaction, or in writing, can also be examined as cues for personality judgement, although this work more often focuses on cue validity over cue utilization. For example, extraversion is correlated with the use of more social process words (i.e., words referring to other people or words indicating social behaviors such as talk, we/us, friend, etc.) in self-narratives, personal essays, and emails (Hirsh & Peterson, 2009; Pennebaker & King, 1999; Oberlander & Gill, 2006).

On social media, extraversion is related to more positive emotion words in Tweets, Facebook status updates, and blogs (Gill et al., 2009; Kern et al., 2014; Sumner et al., 2012; Qiu et al., 2012). A meta-analysis (Chen et al., 2020) that examined studies using text analysis tools (such as Linguistic Inquiry and Word Count, or LIWC) to predict extraversion found that extraversion is related to the use of social process words and positive emotion words. While text analysis using a tool such as LIWC is not used in the current study, written content was coded for positivity/negativity and social themes.

Additionally, a variety of observable behaviors on SNSs have been related to extraversion. One study found that higher levels of extraversion are related to having more Facebook friends (although only up to about 500 friends), while social attractiveness is rated highest when around 300 friends are displayed but evaluated lower with fewer or more friends (Hall & Pennington, 2013; Tong et al., 2008). Extraverts have been found to be more likely to use emoticons and exaggerated spellings (e.g., “whyyyyy”; Hall & Pennington, 2013).

To summarize, due to possible relations to extraversion, positive facial expression, dominant facial expression, smiling, and attractiveness were coded in images. In written content, mentions of others and positive/negative emotion were coded. General profile characteristics such as the number of followers/following were also coded.

Agreeableness

Similar to extraversion, nonverbal cues that have been identified as both valid and utilized for agreeableness include a cheerful facial expression and an attractive and neat appearance (Albright et al., 1997; Berry & Landry, 1997; Funder & Sneed, 1993; Kaurin et al., 2018; Meier et al., 2010, Stopfer et al., 2014; Vazire et al., 2008). In addition to these cues shared with extraversion, cues for agreeableness also include a shorter stride length and more fluent speaking (e.g., Borkenau & Liebler, 1992, 1995; Riggio & Freedman, 1986).

Returning to text analysis, agreeableness has been found to be positively correlated with categories of words indicating social communality and positive emotion (e.g., first-person plural pronouns/references, family, friends, and positive emotions), and negatively correlated with the use of negative emotion words and swear words (Yarkoni, 2010). Again, while these cues may be valid, there has not been research on their utilization. On the other hand, emoji use is utilized and perceived as relating to agreeableness, sincerity, and friendliness (Wall et al., 2016), but it is not clear whether emoji use is a valid cue of agreeableness and was thus examined in the present study. Agreeable Facebook users have been found to update statuses less frequently, specifically posting fewer statuses containing media, music, or news. These statuses also contained fewer words with less variety, however, more agreeable individuals also tended to comment more frequently on other people's posts (Hall & Pennington, 2013).

To summarize, due to possible relations to agreeableness, smiling, positive facial expression, attractiveness, and neatness were coded. In written content, again, mentions of others and positivity/negativity were coded. Additionally, emoji use was coded.

Conscientiousness

For conscientiousness, attractiveness and neatness of appearance are again both valid and utilized cues (Albright et al., 1988; Lyons et al., 2004; Naumann et al., 2009; Nestler et al., 2012). Additionally, however, a less distinct appearance, a more formal appearance, and shorter hair are also cues for conscientiousness (Borkenau & Liebler, 1992, 1995; Lyons et al., 2004; Naumann et al., 2009; Nestler et al., 2012). Looking at body language, valid cues include a self-assured posture and less self-touch (Borkenau & Liebler, 1992, 1995; Lyons et al., 2004; Naumann et al., 2009). Online, more conscientious Facebook users have been found to appear more friendly in profile pictures than less conscientious Facebook users (Hall & Pennington, 2013).

Regarding written communication, more typos and spelling errors lead to perceptions of lower conscientiousness (Vignovic & Thompson, 2010). The use of “textspeak” (e.g., acronyms, g-clippings, unconventional spellings, emoticons) have been linked to perceptions of lower conscientiousness as well (Fullwood et al., 2015). Text analysis has found that more conscientious people use more words relating to achievement and optimism and swear less (Yarkoni, 2010). Additionally, more conscientious Facebook users were found to post less frequently, be less likely to list their favorite media (e.g., movies/books) in the Info section of their page, and have fewer Facebook friends. Positive affect as well as the topic of family in Facebook status updates are associated with conscientiousness (Hall & Pennington, 2013). Swear words, typos, and spelling errors were all coded within the social media profiles for the present study, as well as positive-negative valence and content themes of academics, work, movies/tv, music, art, sports, other hobbies/interests, religion, and politics.

Openness to Experience/Open-mindedness

Nonverbal cues for openness identified by Breil et al. (2021) include self-assured posture, a larger mouth/fuller lips, and longer hair (Borkenau & Liebler. 1992; Hartung & Renner, 2011; Simpson et al., 1993). Specific to SNS behavior, more open Facebook users tend to be alone in their profile pictures (Segalin et al., 2013).

Yarkoni's (2010) meta- text-analysis found that openness was negatively correlated with 37 of the 66 LIWC categories, and positively correlated with only 4 categories. This pattern was interpreted as reflecting a fundamental difference in language style rather than content (Chung & Pennebaker, 2007), such that people higher on openness tend to use more articles, prepositions, and inclusions (e.g., with, and) suggesting that these individuals use high-frequency "function" words at the expense of the fewer "content" words that make up most of the other LIWC categories. Unexpectedly, one content category positively correlated with openness was words relating to death.

Additionally, on Facebook, listing interests in media and art such as music and books in the Likes section of one's profile and in status updates, was associated with higher levels of openness. More open Facebook users commented less frequently on friends' statuses, but had more unique friends comment on their posts, as opposed to the same few friends repeatedly commenting. Posts made by more open Facebook users were also found to use less shorthand/acronyms and less exaggerated spellings. More open targets also tended to post more about politics and less about romantic relationships (Hall & Pennington, 2013). Similarly to extraversion, on Instagram, openness was found to relate to following, and being followed by, more accounts (Barry et al., 2019). Use of textspeak is also related to lower perceptions of openness (Fullwood et al., 2015). Cues coded in the present study included textspeak, followers and following counts, and content pertaining to romantic relationships, politics, and art.

Neuroticism/Negative Emotionality

A cheerful facial expression is a valid and utilized cue that is negatively related to neuroticism. Tense/nervous body language as well as being less attractive, less neat, shorter in height, and less muscular are all cues for neuroticism (Borkenau & Liebler, 1992, 1995; Hirschmüller et al., 2018; Kaurin et al., 2018; Lyons et al., 2004; Naumann et al., 2009; Nestler et al., 2012; Vazire et al., 2008). Vocally, a less expressive voice, less fluent speaking, a less pleasant voice, being more quiet, and speaking less, are all valid and utilized cues for neuroticism (Aronovitch, 1976; Biel et al., 2011; Borkenau & Liebler, 1992; Hirschmüller et al., 2015, 2018). Additionally, the use of laughter in status updates on Facebook (e.g., haha) and exaggerated spellings were found to positively correlate to neuroticism (Hall & Pennington, 2013).

Online, the use of more words relating to anxiety (e.g., worried, fearful, nervous) in Facebook profiles has been correlated to higher levels of neuroticism (Golbeck et al., 2011). Additionally, this research found that words relating to the biological process of ingestions (e.g., eat, dishes, pizza) as well as the Facebook user possessing a last name with more characters, were correlated with neuroticism. Similar research examining word usage on Twitter found individuals with higher levels of neuroticism more often discussed religion, the perceptual processes of hearing and feeling, and used more exclamation marks (Golbeck et al., 2011).

The use of more textspeak has been found to result in higher perceptions of emotional stability compared to less textspeak (Fullwood et al., 2015). Researchers posited that this is likely related to emoticon use, and other textspeak qualities that may be perceived as better at conveying emotion, thus compensating for the lack of FtF emotional cues. Again, the use of textspeak was coded, along with content pertaining to religion, anxiety, negativity, and whether the profile owner was smiling.

Instagram

Having covered cues by trait, it is important to also examine research specific to the social media platforms of interest in this study: Instagram and Twitter. Instagram is a photo-sharing app that was created in 2015 and has an estimated 1.4 billion monthly active users (Statista, 2022). Regarding the content on the platform, one study found 24.2% of pictures uploaded to the platform were “selfies” and 22.4% of photographs were of users posing with at least one other person. Other common photograph categories included food, activities, and gadgets (Hu et al., 2014). There has been a fair amount of research specifically interested in the “selfie,” defined as a portrait a person has taken of oneself, and that are frequently shared on social media (Sorokowski, et al., 2015). Extraversion has been found to be predictive of selfie-posting, as well as posting group selfies (Kim & Chock, 2017; Sorokowka et al., 2016), while several studies have also found narcissism to predict the frequency of selfie-posting (Foz & Rooney, 2015; Sorokowaki et al, 2015; Weier, 2015) as well as the editing of selfies (Kim & Chock, 2017). Although some research suggests the relationship between narcissism and selfie posting is specific to men (Sorokowski et al., 2015), another study found gender differences to be specific to the dimensions of narcissism. Specifically, the dimension of Leadership/Authority was a stronger predictor of selfie posting among women than men, while the dimension of Entitlement/Exploitativeness was a predictor of selfie posting only among men (Weiser, 2015). Selfies provide for a unique type of self-presentation, allowing individuals to present themselves selectively, and have been found to play a central role in performing online identity and shaping the perceptions of others (Van Der Heide et al., 2012). Research on a Chinese social media platform explored personality judgements based specifically on selfies. By coding for selfie-specific cues (e.g., pressed lips, eyes looking at camera, camera height, etc.) and utilizing a Brunswik's lens model analysis, researchers identified cues that reflected the selfie owners' personality traits. The results showed a significant correlation between self-report and aggregated observers' ratings on openness, but not any of the other four main personality dimensions (Qiu et al., 2015). Features of Instagram photos such as hue, brightness, and saturation have also been found to relate to users' personality traits (Ferwerda, et al., 2016).

A couple of recent studies have examined how personality judgements are made on Instagram. Harris and Bardey (2019) had 65 judge participants make ratings of Instagram profiles of four female users and examined mean-level differences between self-ratings and judges' ratings of the Big Five traits. However, they did not report accuracy correlations, and instead compared self-ratings with observer ratings using *t*-tests. The results were inconsistent across accounts and traits, with authors concluding that their statistical testing alone suggested no clear patterns.

Osterholz et al. (2022) used self and informant reports of 102 Instagram users and the ratings of 100 unacquainted judges to examine judgements of the Big Five, self-esteem, and narcissism made on Instagram. Observer ratings corresponded with targets' self-reports for five out of the seven traits, with the exceptions being agreeableness and conscientiousness. Researchers also identified specific cues present on Instagram pages that related to the user's personalities and judge perceptions, which helped inform the selection of cues for the present study and are identified in Tables 3, 4, and 5.

Twitter

Twitter is a microblogging app and website founded in 2006, with an average of 436 million monthly active users (Statista, 2022). Studies have shown that the content of microblogs commonly consists of descriptions of daily routines, reporting news, sharing information, and having conversations (Java et al., 2007; Naaman, et al., 2010). Twitter users most often use the platform to be alerted and find out more about breaking news, keep up with news in general, to tell others what they are doing and thinking about, and to see what others are talking about specifically regarding media (sports, TV shows, live events, etc.; Rosenstiel et al., 2015). A study that looked at personality judgement accuracy specifically on Twitter found that using only the text content of 10 original tweets, judges were able to accurately judge levels of neuroticism and agreeableness, but not conscientiousness, extraversion, or openness (Qiu et al., 2012). Outside the context of Twitter, past research has found that stimuli written by targets from a variety of prompts (e.g., stream of consciousness essays, messages to one's mother, thank you notes to professors, writing about something scary one experienced, writing about one's study habits, etc.) can be used to accurately judge all Big Five personality traits (Holleran & Mehl, 2008; Borkenau et al., 2014; Hall et al., 2016).

The sharing of thoughts and feelings on Twitter could provide more relevant cues for judgements of negative emotionality. It is also possible that the ways in which people engage with others, and share, defend, or argue for their thoughts and opinions, could provide very salient cues for agreeableness. Altogether, Twitter profiles were coded for the amount of humor, and tweets about relationships with others, politics, the user's negative thoughts/feelings, and the user's positive thoughts/feelings including gratitude.

Personality Judgement Accuracy Based on Viewing Instagram and Twitter Profiles

Previous research has found that both Instagram and Twitter can be used to form accurate judgements of personality, however, Instagram provided for significantly more accurate judgements than Twitter, both for distinctive accuracy (b = .08, SE = .02, p < .001) and normativity (b = .27, SE = .04, p < .001; Pedersen, 2020). Target descriptive statistics for this study can be found in Table 1. It is possible that this difference in accuracy can be explained by anonymity. As discussed previously, a lower level of anonymity on a platform is related to more authentic self-presentation. Instagram is owned by Meta (formerly Facebook), and users are encouraged to link their Instagram accounts to their Facebook, decreasing the level of inherent anonymity. If a user wishes to be anonymous on Instagram, they can create an account using a fake name, however, because Instagram is a mobile app, not a website, the phone number of the user is still used to connect the account to the users' contacts. Twitter, however, is not linked to any other social media, and users often partially or fully anonymize their Twitter handles and usernames. Additionally, many of the Twitter profiles collected for a previous study did not feature profile photos of the profile owner (Pedersen, 2020). Thus, the coding of various aspects of anonymity is a main focus of this dissertation.

When examining individual traits, more differences emerged between platforms (Pedersen, 2020; see Table 2). On Instagram, statistically significant normativity and distinctive accuracy was achieved for all of the Big Five traits when analyzed together, however the models for conscientiousness and negative emotionality did not converge when analyzing traits individually, meaning those specific results should not be considered reliable. Significant normativity and distinctive accuracy were achieved for the remaining three traits. On Twitter, distinctive accuracy was only significant for agreeableness and negative emotionality. Assuming that the content of the Instagram profiles is mostly made up of selfies and other photos of the self with others, these results fit with past research. Research on selfies specifically found accurate judgements of openness (Qiu et al., 2015), while research on photographs of targets more broadly has found accurate judgements for extraversion (Naumann et al., 2009). A lack of photos of the self on Twitter may explain the lack of distinctive accuracy for these traits. The traits of agreeableness and negative emotionality were judged with significant distinctive accuracy on Twitter and were the same traits that were found to be judged accurately on Twitter in past research (Qiu et al., 2012). Qiu et al. found that negative emotion words partially mediated the accuracy of judgements of neuroticism. Also, when examining individual cues, the use of sexual words in tweets was negatively related to self-reported agreeableness and negatively related to observer ratings of agreeableness (i.e., cue utilization and validity). This past research, combined with the results of my thesis, provide for a few more cues of interest to be coded: selfies and other photos, negative emotion words, and sexual words. By comparing coded cues both across and between platforms, this study helps to explain why these differences in accuracy of judging specific traits were found between Instagram and Twitter.

Table 1

Target Descriptive Statistics from Pedersen, 2020

	Instagram Targets *M* [95% CI], (*SD*)	Twitter Targets *M* [95% CI], (*SD*)	*t*	*p*
Extraversion	3.48 [3.32, 3.64] (.71)	3.37 [3.20, 3.54] (.72)	1.01	.31
Agreeableness	3.92 [3.79, 4.05] (.56)	3.80 [3.66, 3.94] (.62)	1.33	.18
Conscientiousness	3.57 [3.43, 3.71] (.60)	3.63 [3.47, 3.79] (.68)	-.50	.62
Open-Mindedness	3.85 [3.71, 3.99] (.60)	3.90 [3.76, 4.04] (.59)	-.46	.64
Negative Emotionality	2.85 [2.71, 2.99] (.86)	2.97 [2.83, 3.11] (.90)	-.84	.40

Table 2

Distinctive Accuracy and Normativity of Trait Judgements from Pedersen, 2020

	Normativity *b* (SE)	Distinctive Accuracy *b* (SE)
	Across SNS Type	
Extraversion	1.05 (.09)***	.02 (.02)
Agreeableness	.33 (.03)***	.24 (.02)***
Conscientiousness	.36 (.04)***	.02 (.02)
Negative Emotionality	.63 (.07)***	.06 (.02)**
Open-Mindedness	.39 (.04)***	.04 (.02)**
All Traits	.39 (.03)***	.13 (.01)***
	Instagram	
Extraversion	1.18 (.11)***	.06 (.03)*
Agreeableness	.47 (.04)***	.36 (.03)***
Open-Mindedness	.53 (.05)***	.05 (.02)*
All Traits	.52 (.03)***	.16 (.02)***
	Twitter	
Extraversion	.89 (.11)***	-.02 (.03)
Agreeableness	.20 (.04)***	.14 (.03)***
Conscientiousness	.17 (.07)*	-.007 (.03)
Negative Emotionality	.49 (.09)***	.06 (.03)*
Open-Mindedness	.24 (.05)***	.04 (.02)
All Traits	.27 (.04)***	.08 (.01)***

Note. *b* = regression coefficient from SAM, SE = standard error for that regression coefficient. *** $p < .001$, ** $p < .01$, * $p < .05$.

Study 1 Hypothesis and Research Questions

Study 1 had one main hypothesis, through which I sought to explain the differences in accuracy across platforms found in my thesis, with Instagram profiles providing for more accurate judgements. It was hypothesized that profiles that were coded as highly anonymized would have been judged with less accuracy. Relatedly, profiles that contain more images of the profile owner would have been judged with more accuracy. Overall, this was predicted to help explain why Instagram provides for higher levels of accuracy. The number of pictures of the profile owner was included in the overall calculation of profile anonymity. If, as predicted, Instagram profiles were consistently coded as less anonymous (with more images of the profile owner), it was predicted that lower anonymity (by way of the Good Information moderator) would lead to greater accuracy. The rest of the analyses in Study 1 were largely exploratory, with the goal of identifying valid and utilized cues of personality on Instagram and Twitter through the application of Brunswik's Lens Model.

Chapter 3: Study 1 Method

Coding Social Media Profiles

The first step within this project was to code the 102 collected social media profiles for a variety of cues that may be relevant to the process of personality judgement accuracy. Cues were selected through a combination of examining past research findings, questions prompted throughout my thesis project, and consideration of how Instagram and Twitter differ as platforms. While many types of cues can be found across the platforms, there are also key differences between the platforms that may contribute to differences in judgement accuracy, so each profile type's unique cues were also coded. Table 3 shows which cues were coded across platforms, while Tables 4 and 5 show cues specific to Instagram and Twitter, respectively. The first cue category is Anonymity, which is a concept central to this project. However, the concept of coding for cues relating to anonymity is relatively novel, and thus there is very little associated research. Beyond this first category, however, the relevant or associated research to specific cues is provided in the tables, organizing the information found throughout the literature review.

Independent coders consisted of myself and trained research assistants. Training ensured that the meaning of cues and codes were clear, as well as that profiles were coded in a consistent order. This order and more details about the coding process can be found in the Codebook, located within Appendix A. Each profile was coded by three coders. Most codes are objective, and coders reached a consensus on their ratings. In situations in which coders disagreed on their ratings of these objective cues, I examined the discrepancy and, with any necessary input from research assistants, determined the final code. There were also subjective ratings, specifically within the Profile Content categories, in which certain types of content were rated on a 5-point Likert scale ranging from 1 (*not at all*) to 5 (*very much*).

Table 3

Cues on Both Instagram and Twitter

Cues and Cue Categories	Code	Relevant Past Research
Anonymity		
Profile picture seemingly of owner	Yes/No	DeAndrea & Walther, 2011; Fullwood et al., 2016; Osterholz et al., 2022; Toma et al., 2008
If no, content of profile picture	Free response	
Level of anonymity of profile owner picture	1 clearly of face, owner only 2 face unclear (far away/ filtered/ distorted/partially hidden), owner only 3 clearly of face, but with others 4 unclear face, and with others 5 avatar, drawing, or other artistic representation of owner 6 image not of owner	
Profile owner's name present	1 first and last 2 just first 3 other 4 no name	
Text in place of name, if applicable	Free response	
Level of username anonymity, pertaining to name	1 include full first AND last name 2 include full first OR last name 3 include portions of first and/or last name 4 seemingly includes nickname/misspellings of name(s) 5 seemingly no inclusion of name	
Level of username anonymity, pertaining to secondary information	1 contains identifying information such as location, title, birthyear, etc. 2 contains no identifying information	

Anonymity level in bio	1 (a lot of identifying information, such as specific location, age, school, job, names/links to family/significant others) to 5 – (no identifying information)	
Personal-ness of bio	1 (most personal) – 5 (least personal)	
Location specificity	1 – Town 2 – State 3 – Region (e.g., PNW) 4 – Country (including flag emojis) 5 – No location information	
Links/info about other SNS in bio	Numeric	
Basic Profile Characteristics		
Number of Following	Numeric	Amichai-Hamburger & Vinitzky, 2010; Barry et al., 2019; Gosling et al., 2011; Hall & Pennington, 2013; Ong et al., 2011; Tong et al., 2008.
Number of Followers	Numeric	
Presence of bio	Yes/No	
Profile Owner Appearance (if applicable, using all available photos)		
Smiling	1 (not at all) – 5 (very much)	Albright et al, 1997; Borkenau et al., 2009; Funder & Sneed, 1993; Meier et al., 2010; Schultheiss & Brunstein, 2002; Stopfer et al., 2014
Positive facial expression	1 (not at all) – 5 (very much)	Borkenau & Liebler, 1992; Back, Schmukle, & Egloff, 2010; Kaurin et al., 2018
Neutral facial expression	1 (not at all) – 5 (very much)	
Negative facial expression	1 (not at all) – 5 (very much)	
Dominant facial expression/pose	1 (not at all) – 5 (very much)	Berry & Hansen, 2000; Borkenau & Liebler, 1992, 1995; Hartung & Renner, 2011; Petrican, et al., 2014

Stylish (clothes, hair, makeup)	1 (not at all) – 5 (very much)	Borkenau & Liebler, 1992, 1995; Nestler et al., 2012; Stopfer et al., 2014
Attractive	1 (not at all) – 5 (very much)	Berry & Landry, 1997; Kaurin et al., 2018; Kenny et al., 1992; Meier et al., 2010; Naumann et al., 2009; Nestler et al., 2012; Osterholz et al., 2022;Vazire et al., 2008
Neat	1 (not at all) – 5 (very much)	Albright et al., 1997; Hartung & Renner, 2011; Kaurin et al., 2018; Lyons et al., 2004; Meier et al., 2010; Nauman et al., 2009; Vazire et al., 2008
Posed	1 (not at all) – 5 (very much)	Nauman et al., 2009; Qiu et al., 2015
Candid	1 (not at all) – 5 (very much)	
Perceived Age	Numeric	
Profile Content (Written)		
Bio word count	Numeric	
Bio emoji count (including name)	Numeric	Wall et al., 2016
Swear words	Numeric	Golbeck et al.,2011; Qiu et al., 2012; Yarkoni, 2010
Sexually explicit words	Numeric	
Initialisms/Acronyms	Numeric	Fullwood et al., 2015
Exaggerated spellings (seemingly purposeful)	Numeric	Fullwood et al., 2015; Hall & Pennington, 2013
Misspellings (seemingly accidental)	Numeric	Vignovic & Thompson, 2010
Profile Content (Images)		

Self-images/selfies	Numeric	Foz & Rooney, 2015; Kim & Chock, 2017; Qiu et al., 2015; Sorokowaki et al, 2015; Sorokowka et al., 2016; Weier, 2015
Images of self with others	Numeric	Hall & Pennington, 2013
Images of only others	Numeric	
Number of unique others across posts	Numeric	Hall & Pennington, 2013
Number of images without people	Numeric	
Number of videos	Numeric	

Table 4

Cues on Instagram

Cues	Code	Relevant Past Research
Number of story highlights	Numeric	Osterholz et al., 2022
Number of posts containing multiple images	Numeric	Osterholz et al., 2022
Number of images with animals	Numeric	Hagan et al., 2017
Images pertaining to Academics	1 (not at all) – 5 (very much)	
Images pertaining to Work	1 (not at all) – 5 (very much)	
Images pertaining to Movies/TV	1 (not at all) – 5 (very much)	
Images pertaining to Music	1 (not at all) – 5 (very much)	Ferwerda & Tkalcic, 2018
Images pertaining to Art	1 (not at all) – 5 (very much)	
Images pertaining to Sports/Fitness	1 (not at all) – 5 (very much)	Ferwerda & Tkalcic, 2018
Images pertaining to Other Hobbies/Interests	1 (not at all) – 5 (very much)	
Images pertaining to Religion	1 (not at all) – 5 (very much)	
Images pertaining to Politics	1 (not at all) – 5 (very much)	
Number of images outdoors	Numeric	Osterholz et al., 2022
Number of images with crowds	Numeric	

Number of images with imbedded text	Numeric	Osterholz et al., 2022
Number of photos of inanimate objects	Numeric	

Table 5

Cues on Twitter

Cues and Cue Categories	Code	Relevant Past Research
Profile format type	1 – full web version 2 – partial/mobile	
Tweets	Numeric	
Likes	Numeric	
Banner photo	Yes/No	
Banner photo content (can be multiple)	1 People 2 Animals 3 Nature/Outdoors 4 Art 5 Quote 6 Other (with description)	
Joined Date	Free response	
Birthday included	Yes/No	
Number of photos/videos in sidebar	Numeric	
Pinned tweet	Yes/No	
Pinned tweet content	Free response	
Number of images	Numeric	
Original tweets in screenshot	Numeric	
Likes on original tweets	Numeric	
Replies to original tweets	Numeric	
Retweets on original tweets	Numeric	
Retweets in screenshot	Numeric	
Number of times retweeted tweets have been retweeted	Numeric	
Written Content		
Positive Emotion		Golbeck et al., 2011; Gill et al., 2009; Kern et al., 2014; Nowson, 2010; Qiu et al., 2012; Sumner et al., 2012; Yarkoni, 2010
- General positivity	1 (not at all) – 5 (very much)	
- Optimism	1 (not at all) – 5 (very much)	

- Achievement	1 (not at all) – 5 (very much)	Nowson, 2010; Yarkoni, 2010
- Gratitude	1 (not at all) – 5 (very much)	
Negative Emotion		Golbeck et al., 2011; Qiu et al., 2012; Yarkoni, 2010
- General negativity	1 (not at all) – 5 (very much)	
- Stress/Anxiety	1 (not at all) – 5 (very much)	Nowson, 2010
- Sadness	1 (not at all) – 5 (very much)	Qiu et al., 2012; Yarkoni, 2010
- Anger	1 (not at all) – 5 (very much)	Qiu et al., 2012; Yarkoni, 2010
Humor		
- General amount of humor	1 (not at all) – 5 (very much)	Hall et al., 2014
- Memes	1 (not at all) – 5 (very much)	
- Sarcasm	1 (not at all) – 5 (very much)	
Social Processes		Golbeck et al., 2011; Hirsh & Peterson, 2009; Pennebaker & King, 1999; Nowson, 2010; Oberlander & Gill, 2006; Yarkoni, 2010
- Pertaining to non-romantic relationships	1 (not at all) – 5 (very much)	
- Pertaining to romantic relationships	1 (not at all) – 5 (very much)	
- Mentions of Specific Others (seemingly known)	Numeric	Yarkoni, 2010
- Mentions of Specific Others (seemingly unknown e.g., celebrities)	Numeric	
- Mentions of Generic Others/Groups	Numeric	
Pertaining to Academics	1 (not at all) – 5 (very much)	Nowson, 2010; Yarkoni, 2010
Pertaining to Work	1 (not at all) – 5 (very much)	Nowson, 2010; Qiu et al., 2012; Yarkoni, 2010
Pertaining to Movies/TV	1 (not at all) – 5 (very much)	Nowson, 2010; Qiu et al., 2012
Pertaining to Music	1 (not at all) – 5 (very much)	Yarkoni, 2010
Pertaining to Art	1 (not at all) – 5 (very much)	
Pertaining to Sports	1 (not at all) – 5 (very much)	
Pertaining to Other Hobbies/Interests	1 (not at all) – 5 (very much)	
Sexual content	1 (not at all) – 5 (very much)	Qiu et al., 2012; Yarkoni, 2010
Political content	1 (not at all) – 5 (very much)	Hall & Pennington, 2013

Religious content	1 (not at all) – 5 (very much)	Golbeck et al., 2011; Qiu et al., 2012; Yarkoni, 2010
Emojis	Numeric	Wall et al., 2016

Targets

Target data collection was a part of my thesis project (Pedersen, 2020). Targets were recruited from SONA as well as through email, social media posts, and posters placed around campus and the town of Pocatello, Idaho. It was stated clearly in the study description that participants should be active and experienced Twitter or Instagram users with public profiles who were at least 18 years of age. Community participants were entered to win a $25 Amazon gift card as an incentive for participation. Additionally, near the end of data collection, when only male targets were being recruited in order to ensure gender diversity, all qualified participants who completed the study were given a $5 Amazon gift card. Social media profiles were recorded through screenshots. On Instagram, 12 posts were recorded. This simulates the number of photos shown on the average phone screen when viewing the app. On Twitter, 12 tweets were recorded, not including a pinned tweet if present, but including retweets. For both SNSs, the posts recorded were the most recent posts. Targets completed a variety of self-report measures, but only the Big Five Inventory-2 is relevant to this dissertation[1].

[1] Additional measures included the Social and Economic Conservatism Scale (SECS; Everett, 2013), Satisfaction With Life Scale (SWLS; Diener et al., 1985), political party affiliation, and Intelligence. Intelligence was measured by three items from Human et al., (2014) that were interspersed randomly into the BFI-2. Additionally, two questions were asked regarding whether they believed the SNS profile they provided portrayed them 1) in a positive way and 2) in an authentic way.

Measures

Target's completed self-reports of the Big Five Inventory 2 (BFI-2; Soto & John, 2017). The 60-item BFI-2 is a self-report measure of the Big Five personality domains: Extraversion, Agreeableness, Conscientiousness, Negative Emotionality, and Open-Mindedness (Soto & John, 2017). Items are rated on a 5-point scale from 1 (*disagree strongly*) to 5 (*agree strongly*). The BFI-2 has good reliability with Cronbach's alpha reliabilities of .83 to .90 for the five subscales and .87 for the overall measure (Soto & John, 2017). For these targets, reliabilities ranged from .81 to .92 for the five subscales and .85 for the overall measure.

Judges completed a self-report of the BFI-2 as well as other-report versions for each of the Target profiles viewed. Judges were asked questions pertaining to their own social media use, including how often they use social media and how often they post/share content on social media. Additionally, judges completed a general demographics questionnaire including gender, age, race, ethnicity, level of education, marital status, and religious affiliation,

Judge Ratings

For Study 1, judge ratings from my thesis project were used to analyze the utilization of cues. For my thesis, 150 target profiles were collected. Of those, 102 consented to their profiles being used in future, unplanned research. Each target profile was rated by 10 judges, and each judge rated six targets, so the original judge sample size was 268 (61% female, 39% male, 1 participant did not identify), majority White (76%; 8% White with specified Hispanic ethnicity, 7% Black, 3% Asian, 3% identified as "multiple" or "mix/mixed," 1% Black with specified Hispanic ethnicity, and 1% Native American), between the ages of 18 and 70 (M_{age} = 29.42, SD_{age} = 11.98). Removing the ratings of targets whose profiles were not used in this study did not alter the judge sample size. One hundred and thirty-eight of these participants were recruited through SONA, and 130 were recruited through Amazon's Mechanical Turk. All participants completed the study online. Participants recruited through SONA were given class credit/extra credit for participating. Participants recruited through MTurk were monetarily compensated, receiving $1 for completing the study. Again, judges completed a variety of measures but relevant to this study is the Big-Five Inventory-2, short form. The 30-item BFI-2-S is a shortened version of the BFI-2. Due to the potential for participant fatigue, as judges were required to complete the same measures multiple times for different targets, the BFI-2-S was chosen over the original BFI-2. The scale was modified to an other-report version so that judges were asked to rate the targets on each item. Within the current study, internal reliability was slightly lower for the five subscales (α's = .68-.83) but was adequate for the overall measure (α = .75).

Lens Model Analysis

Once all profiles were coded, for each cue and trait, a) the extent to which the cues correlate with the targets' self-reported personalities (cue validity), and b) the extent to which cues correlate with judge's personality ratings (cue utilization) were examined. To measure cue validity, the targets' personalities were correlated with the independently coded cues for each trait. To measure cue utilization, the aggregated judges' ratings were correlated with these cues. The initial analysis plan involved using the lensModel function in the multicon R package, which is a multiple regression approach to Lens Model Analysis. However, with 49 coded cues for Instagram and 85 for Twitter serving as predictors and only 55 BFI scores for Instagram/45 BFI scores for Twitter (self-report for cue validity and other report for cue utilization) serving as observations in the multiple regression models, the models suffered from overfitting/overspecification, as indicated by singular fit errors and multicollinearity issues. Potential strategies to avoid overfitting include 1) collecting more observations and 2) reducing the number of predictors (Babyak, 2004). Since collecting more observations would mean collecting more social media profiles, including target self-reports, judgements, and coded cues, this was beyond the scope of this project. However, reducing the number of predictors via principal component analysis (PCA) is common for lens model analysis, and upon further investigation, should have been included in the initial analysis plan.

In order to obtain reliable estimates and identify cues to use for training in Study 2, the data were examined using both a principal component analysis (PCA) approach and a basic zero-order correlational approach to lens model analysis. As the main goal was to reduce the number of intercorrelated observed variables, and there was no theoretical model of underlying factors, principal component analysis was the appropriate approach over factor analysis. Basic correlations were also utilized in order to identify individual specific cues for ease of training in Study 2.

Chapter 4: Study 1 Results

Study 1

Descriptive Statistics

Descriptive statistics for the cues across platforms and on Instagram and Twitter individually can be found in Tables 6, 7, and 8, respectively. Overall interrater reliability, using the two-way random effect models to evaluate absolute agreement, was moderate on Twitter, k = 0.66, p < .001, 95% CI [.64, .67] and good on Instagram, k = 0.81, p < .001, 95% CI [.79, .82].

Table 6

Cues Across Platforms

Cue	Instagram Mean (SD)	Twitter Mean (SD)	Across SNS Mean (SD)	Instagram ICC (for subjective cues)	Twitter ICC (for subjective cues
Anonymity					
Anonymity composite score (unstandardized)	10.82 (6.72)	15.41 (4.70)	12.91 (6.29)		
Anonymity in profile picture	2.07 (1.45)	2.11 (1.45)	2.08(1.43)		
Name anonymity	1.48 (0.72)	1.67 (0.71)	1.56 (0.71)		
Username anonymity	4.68 (1.64)	4.00 (1.36)	4.35 (1.64)		
Location anonymity	4.13 (1.43)	3.16 (1.89)	3.67 (1.71)		
Anonymity in Bio	3.81 (1.07)	4.04 (1.31)	3.92 (1.18)	0.68	.61
Personalness in Bio	3.73 (0.93)	3.60 (1.40)	3.67 (1.16)	0.54	.57
Other SNS Links	0.69 (0.41)	0.33 (0.48)	0.37 (0.60)		
Selfies	3.61 (2.78)	0.57 (1.13)	2.24 (2.66)		
Images of self with others	4.15 (3.08)	0.59 (1.21)	2.55 (2.99)		
Profile Features/Content					
Followers	724.83 (559.58)	335.87 (305.13)	548.03 (499.04)		
Following	704.81 (569.14)	368.78 (371.47)	552.07 (515.18)		

Bio Word Count	7.06 (6.85)	7.16 (7.51)	7.10 (7.12)		
Bio Emoji Count	1.83 (2.70)	1.27 (2.10)	1.57 (2.45)		
Videos	0.87 (1.79)	2.13 (1.87)	1.44 (1.92)		
Swear words	0.07 (0.33)	1.22 (1.43)	0.59 (1.14)		
Images of only others	0.90 (1.60)	3.82 (3.94)	2.22 (3.24)		
Images without people	3.02 (3.56)	1.82 (1.81)	2.47 (2.94)		
Appearance					
Smiling	3.41 (1.20)	3.20 (1.69)	3.31 (1.44)	.83	.82
Positive facial expression	3.75 (1.06)	3.78 (1.41)	3.76 (1.22)	.87	.68
Neutral facial expression	2.65 (1.20)	2.88 (1.81)	2.75 (1.49)	.70	.70
Negative facial expression	1.16 (0.33)	1.32 (0.65)	1.23 (0.50)	.53	.37
Dominant facial expression/pose	2.03 (0.99)	1.98 (1.46)	2.01 (1.21)	.63	.37
Stylish	3.41 (0.96)	3.02 (1.19)	3.24 (1.08)	.74	.30
Attractive	3.36 (0.87)	3.63 (0.98)	3.48 (0.92)	.67	.41
Neat	3.30 (0.83)	3.32 (1.17)	3.31 (0.98)	.73	.40
Posed	4.07 (0.64)	4.34 (0.88)	4.19 (0.76)	.54	.05
Candid	1.71 (0.62)	1.78 (1.29)	1.74 (0.97)	.49	.22
Themes					
Academics	1.71 (1.00)	1.84 (1.08)	1.77 (1.04)	.77	.63
Work	1.29 (0.68)	1.25 (0.61)	1.27 (0.65)	.22	.25
Movies/TV	1.25 (0.58)	1.64 (1.02)	1.43 (0.83)	.62	.73
Music	1.38 (0.83)	1.79 (1.22)	1.54 (1.05)	.72	.83
Art	1.68 (0.97)	1.26 (0.61)	1.49 (0.85)	.40	.31
Sports/Fitness	1.83 (1.08)	2.20 (1.53)	2.00 (1.31)	.87	.83
Other hobbies/interests	2.30 (1.24)	1.74 (1.03)	2.05 (1.18)	.38	.61
Religion	1.33 (0.80)	1.29 (0.78)	1.31 (0.79)	.79	.81
Politics	1.06 (0.28)	1.71 (1.39)	1.35 (0.98)	.53	.92

Table 7

Cues on Instagram

Cues	Means (SD)
Number of story highlights	0.93 (1.87)
Number of multiple posts	4.24 (3.00)
Unique others across posts	7.27 (11.13)
Images with crowds	0.76 (1.03)

Images with animals	0.75 (1.18)
Images outdoors	4.95 (3.50)
Images with embedded text	1.38 (2.12)
Images of inanimate objects	1.84 (2.77)

Table 8

Cues on Twitter

Cues	Means (SD)	ICC (for subjective cues)
Likes	6283.33 (8389.72)	
Media in sidebar count	78.67 (144.13)	
Original tweets	3.84 (3.43)	
Likes on original tweets	160.70 (585.84)	
Replies on original tweets	1.56 (2.60)	
Retweets on original tweets	71.12 (305.04)	
Retweets total	8.53 (3.43)	
# Under 10 RT	1.71 (2.02)	
# 10-100 RT	1.00 (1.21)	
# 100-1k RT	1.73 (2.07)	
# 1k-10k RT	1.57 (1.37)	
# 10k-100k RT	2.18 (2.30)	
# Above 100k RT	0.49 (0.74)	
Content		
Sexually explicit words	0.22 (0.56)	
Emojis	4.38 (4.06)	
Initialisms/acronyms	1.20 (1.32)	
Exaggerated/slang spellings (purposeful)	1.67 (1.80)	
Misspellings/typos	0.04 (0.21)	
Emotional Themes		
General positivity	3.00 (1.02)	.61
Optimism	1.64 (0.86)	.38
Achievement	1.62 (1.17)	.63
Gratitude	1.38 (0.68)	.50
General negativity	2.78 (1.11)	.41
Stress/anxiety	1.58 (0.78)	.32
Sadness	2.00 (1.15)	.40
Anger	1.49 (0.89)	.37
General humor	2.27 (0.99)	.42
Memes	1.49 (0.59)	.33
Sarcasm	1.78 (0.85)	.46
Social Processes		

Pertaining to nonromantic relationships	2.02 (0.78)	.10
Pertaining to romantic relationships	2.09 (1.12)	.65
Mentions of specific others	3.60 (3.74)	
Mentions of generic others	1.73 (1.78)	

Hypothesis 1

It was hypothesized that profiles that were coded as highly anonymized would have been judged with less accuracy. Relatedly, profiles that contain more images of the profile owner would have been judged with more accuracy, helping to explain differences in accuracy between Twitter and Instagram. Across targets, a composite anonymity score comprised of the variables identified in Table 3 plus Selfies/Self-Images and Images of the Self with Others was created. Two relevant cues were binary, indicating yes/no responses. One such cue had to do with whether the profile owner was pictured in the profile picture or not. This cue was recoded such that yes = 1 and no = 0, and was then added into the total number of pictures of the profile owner in other places (i.e., cues of selfies/self-images and images of the self with others). The other binary cue had to do with the presence of any identifying information within the username aside from name information (e.g., location, birthyear, etc.). This was combined with the other cue that indicated identifying information in the username, such that an overall higher score indicated less identifying information (and thus, more anonymous). Then all cues were standardized using z-scores before being combined into the composite anonymity score. All cues were additive except for the cues of Links/Information about other SNSs and Images of the Profile Owner, wherein higher numbers indicated less anonymity, and were thus reverse scored before being added into the composite score. Internal consistency for this score was not acceptable ($\alpha = .47$), indicating that the items, chosen for their face validity, did not correlate to one another. Two items slightly increased overall internal consistency when dropped from the composite score. These items were the specificity of the user's name ($\alpha = .48$ when dropped) and username anonymity ($\alpha = .51$ when dropped.) This low level of internal reliability is perhaps not surprising, as anonymity as operationalized here is not theorized as some latent variable, but as a collection of online behaviors (or lack of behaviors) that can be expected to vary independently from one another. It was not predicted that individuals who, for example, do not have their full name in their username would also not post pictures of themselves. Nonetheless, this composite score, wherein higher overall scores represented more anonymous behaviors across these relatively uncorrelated individual variables, was analyzed as originally planned. Negative scores indicate levels below the average after standardization. Surprisingly, Instagram profiles ($M = -0.47$, $SD = 3.93$) and Twitter profiles ($M = 0.57$, $SD = 3.27$) did not differ significantly in their levels of anonymity, $t(97) = 1.42$, $p = .16$, 95%, CI [-2.509, 0.413], representing a small effect, $d = .28$ (see Figure 2). This indicates already that the difference in accuracy between profile types is not likely explained by differences in anonymity. When examining the components of the composite anonymity score individually using either *t*-tests for interval data or Mann-Whitney U tests for ordinal variables, Twitter was more anonymous, although nonsignificantly, for all components except for username anonymity and location specificity. For username anonymity, Instagram profiles ($M = 4.68$, $SD = 1.63$, $Mdn = 4$, $n = 54$) were significantly more anonymized than Twitter profiles ($M = 4.00$, $SD = 1.36$, $Mdn = 3$, $n = 45$), $U = 1513.50$, $p = .03$ representing a small effect using the Glass rank biserial coefficient, $r_{rb} = .25$ (see Figure 3). Twitter users more frequently used usernames that included their full first and last name (46.7% on Twitter, 33.3% on Instagram), just their first or last names (31.1% on Twitter, 18.5% on Instagram) and

Instagram users more frequently used usernames that included portions of their name (14.8% on Instagram, 8.8% on Twitter), nicknames (7.4% on Instagram, 2.2% on Twitter) or no presence of their names (25.9% on Instagram, 11.1% on Twitter). Similarly, for location specificity, Instagram profiles (*M* = 4.13, *SD* = 1.42, *Mdn* = 5, *n* = 54) were significantly more anonymous than Twitter profiles (*M* = 3.16, *SD* = 1.89, *Mdn* = 4, *n* = 45), *U* = 1570.00, *p* = .004, representing a medium effect, r_{rb} = .29 (see Figure 4). Instagram users more frequently mentioned the country (3.7% on Instagram, 2.2% on Twitter) or state they are located in (20.4% on Instagram, 11.1% on Twitter) or did not mention location at all (70.4% on Instagram, 44.4% on Twitter), and Twitter users more frequently specified what town they are located in (42.2% on Twitter, 5.6% on Instagram). Twitter prompts users to fill out their location information within their bio, while Instagram does not, which helps explain this difference.

Figure 2

Anonymity Composite on Instagram and Twitter

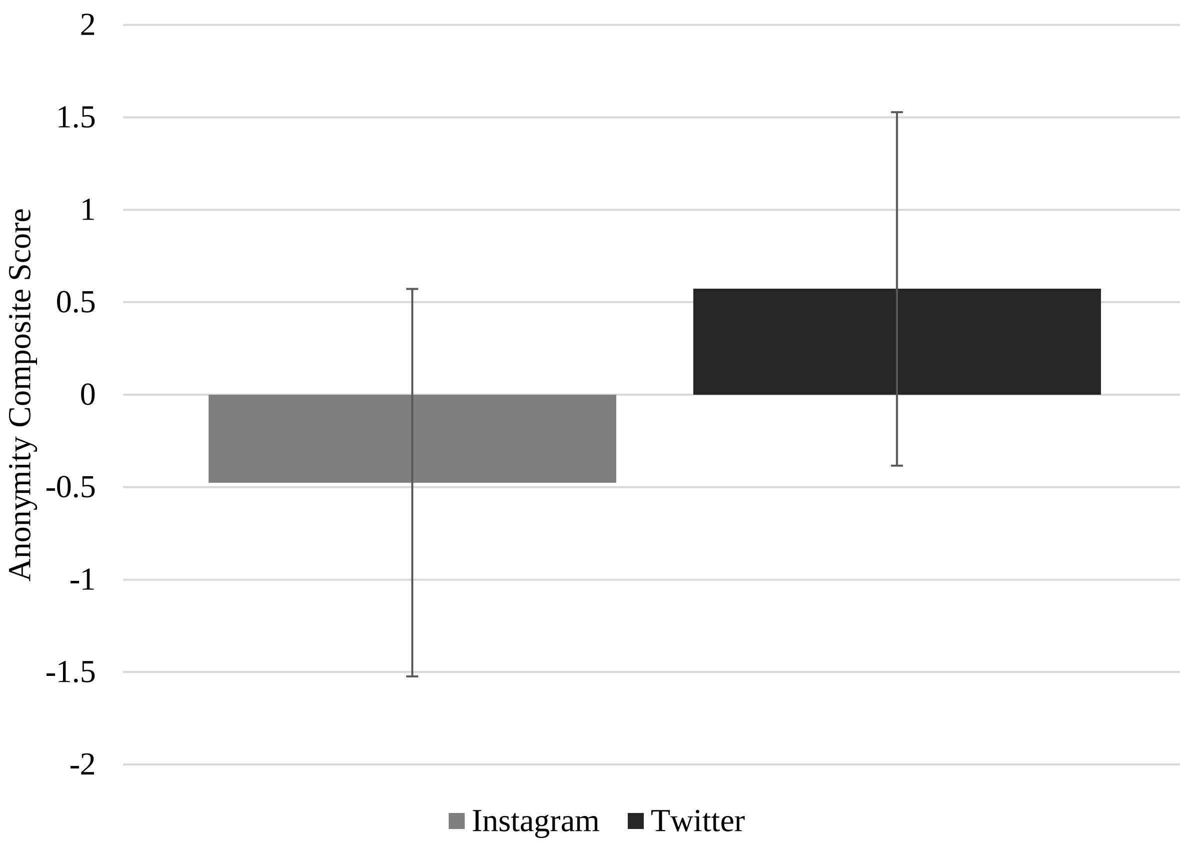


Figure 3

Username Anonymity on Instagram and Twitter

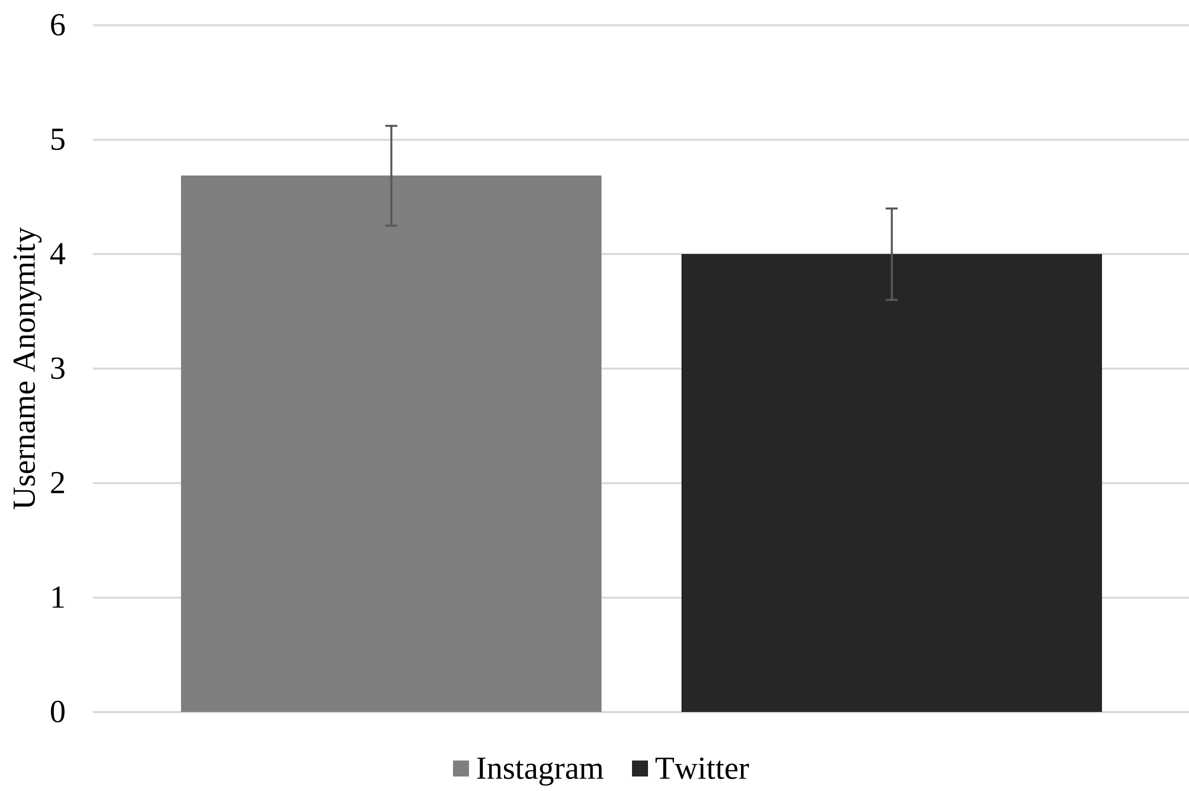
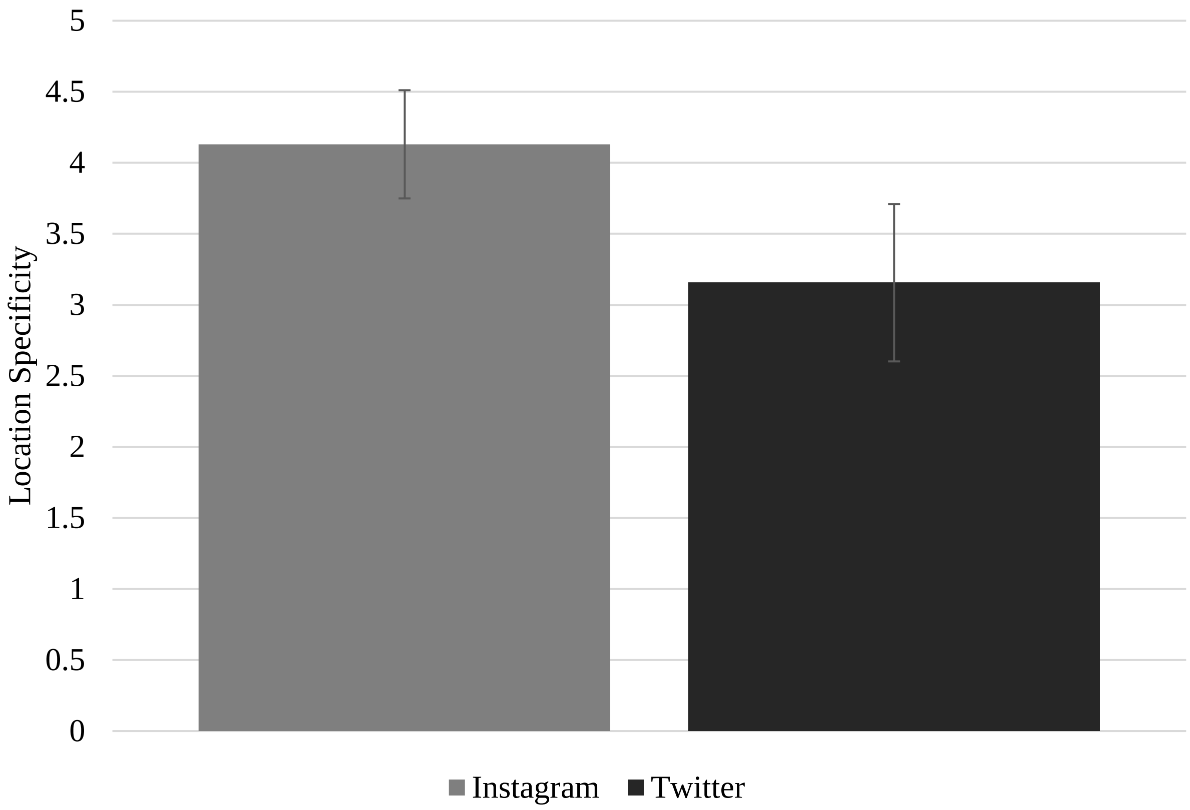


Figure 4

Location Specificity on Instagram and Twitter



Across platforms, entering the composite anonymity score into the Social Accuracy Model as a moderator revealed a significant interaction between anonymity and normativity (b = -0.01, SE = 0.001, p = .026) but not distinctive accuracy (b = -0.005, SE = 0.004, p = .238), with lower levels of anonymity predicting more normatively accurate judgements.. Entering both anonymity and SNS platform type into the Social Accuracy Model as moderators simultaneously revealed a significant three-way interaction between anonymity, SNS profile type, and normativity (b = -0.03, SE = 0.014, p = .035) but not distinctive accuracy (b = -0.006, SE = 0.008, p = .465). To explore this, the effect of anonymity on accuracy on each SNS platform type separately was examined. On Instagram, the interactions were not significant. On Twitter however, similar to the analysis across platforms, there was a significant interaction between anonymity and normativity (b = -0.03, SE = 0.012, p = .012), but not distinctive accuracy (b = -0.007, SE = 0.006, p = .265). This suggests that judges are incorrectly perceiving targets who present more anonymously as being less similar to the average person, but only on Twitter.

Principal Component Analysis

First, correlations between cues were examined to ensure the data were appropriate for principal component analysis. Correlation tables for Instagram and Twitter cues are presented in Table B1 and Table B2 in Appendix B. Bartlett's tests of sphericity were used to confirm that the correlation matrices for the cues on each platform were significantly different from an identity matrix (where all correlation coefficients are zero). Bartlett's test was significant, indicating the data was suitably correlated for PCA, for both Instagram (χ^2 (1176) = 2516.8, p <.001) and Twitter (χ^2 (3321) = Inf, p <.001; note that this result likely indicates that the correlation matrix has some level of singularity also known as multicollinearity, which is not a problem for PCA and is a common issue in qualitative variable coding. In order to determine the appropriate number of principle components to extract, scree plots and eigenvalues were examined. Neither scree plot (Figure B1 and Figure B2 in Appendix B) provided a clear cut-off point, although likely between the eigenvalues of 1 and 2. The classical Kaiser-Guttman criterion approach would recommend retaining all components with an eigenvalue greater than one, however this approach is widely considered too liberal as it tends to overestimate the number of factors (e.g., Zwick & Velicer, 1986). Methods for accurately determining the "correct" number of components are greatly debated, with many concluding there is no ideal solution to the problem (e.g., Cangelosi & Goriely, 2007; Ferre, 1995). However, when the goal is reduction of multicollinearity, as it is in this case, some statisticians recommend erring on the side of extracting too many components (Field, 2012). Additionally, since only components with the specific qualities of being valid and unutilized in the subsequent Lens Model Analysis would be useful in determining Study 2 methodology, the liberal Kaiser-Guttman criterion approach was utilized.

This resulted in 16 principal components being extracted on Instagram and 23 on Twitter. When examining the correlations between components when using an oblique rotation, there were very weak relationships between components (all $r < .25$), so orthogonal rotation was used to extract component values. To get an idea of the component relationships, all cues with loadings > .4 for each of the components are presented in Appendix B. The component values were then used as the cue values in a lens model analysis using the lensModel function in the multicon R package, which is no longer available on current versions of R.

On Instagram, seven out of the sixteen factors were either valid, utilized, or both for at least one personality trait. These results are presented in Table 9. In general, many invalid cue components were utilized, and only two valid components were identified. Principal component 2, which included cues of a positive facial expression and smiling (and relatedly a less neutral, less negative, and less dominant facial expression), images of the self with others, less selfies, a more neat appearance, and more content pertaining to sports and fitness, was both a valid and utilized cue component for higher agreeableness and lower negative emotionality. This cue component was also utilized for higher ratings of extraversion and conscientiousness, although invalid, meaning this component was not related to actual self-reported levels of these traits. The only valid and unutilized cue component, and thus of potential interest for training, was principal component 5, which included cues of more video posts, more posts pertaining to music, more links/information about other social media accounts, and more photos of inanimate objects. This component was found to be valid for lower levels of open-mindedness, but was only utilized for lower ratings of agreeableness and consciousness.

Table 9

Instagram PCA Lens Model Results

Principal Component	Valid	Utilized
1	X	Extraversion, Conscientiousness
2	Agreeableness, Negative emotionality (-)	Extraversion, Agreeableness, Conscientiousness, Negative emotionality (-)
3	X	X
4		Extraversion, Agreeableness, Negative emotionality (-)
5	Open-mindedness (-)	Agreeableness (-), Conscientiousness (-)
6	X	Open-mindedness
7	X	Agreeableness (-), Conscientiousness (-), Negative emotionality
8	X	X
9	X	Extraversion, Negative emotionality (-)
10	X	X
11	X	X
12	X	X
13	X	X
14	X	X
15	X	X
16	X	X

Note. X's indicate non-significance. (-) indicates that the relationship between the principal and the trait is negative.

On Twitter, 10 out of the 23 factors were either valid, utilized, or both for at least one personality trait. These results are presented in Table 10. Again, there were more utilized cue components than valid ones, indicating the use of invalid cues. Perhaps surprisingly, unlike on Instagram, there were no valid and utilized cue components. This could help to explain the pattern found in my thesis study of lower levels of accuracy on Twitter. Three cue components were valid and unutilized, indicating potential target areas for training. Principal component 4, which included more tweets, more following/followers, more media posted, and more emojis in the bio, was a valid cue for lower conscientiousness. Principal component 10, which included more mentions of generic groups of others, more content pertaining to nonromantic relationships, politics, and work, and more anger, was a valid cue for higher conscientiousness. This cue component was utilized, however, for lower ratings of agreeableness and open-mindedness. Lastly, principal component 18, which included fewer spelling errors and less identifying information in the username, was a valid cue for lower levels of open-mindedness.

Table 10

Twitter PCA Lens Model Results

Principal Component	Valid	Utilized
1	X	X
2	X	X
3	X	X
4	Conscientiousness (-)	X
5	X	X
6	X	X
7	X	X
8	X	X
9	X	X
10	Conscientiousness	Agreeableness (-), Open-mindedness (-)
11	X	Negative emotionality (-)
12	X	X
13	X	Conscientiousness (-)
14	X	Open-mindedness
15	X	X
16	X	Agreeableness (-), Conscientiousness (-), Open-mindedness (-), Negative emotionality
17	X	X
18	Open-mindedness (-)	X
19	X	Extraversion
20	X	Extraversion (-), Conscientiousness (-), Negative emotionality
21	X	Negative emotionality
22	X	X
23	X	X

Note. X's indicate non-significance. (-) indicates that the relationship between the principal and the trait is negative.

Basic Correlational Analyses

In order to identify specific cues for training, a basic correlational approach to Lens Model Analysis was also utilized. Results for significant valid and/or utilized cues on Instagram and Twitter are presented in Tables 11-20. Cues that are both valid and utilized (in the same direction) are presented in the same row.

Table 11

Cues to Extraversion on Instagram

	Valid *r*	Utilized *r*
Neat	**.34***	**.40****
Stylish	**.31***	**.31***
Images of self with others	**.29***	**.34***
Positive facial expression	**.28***	**.39****
Images without people	**-.28***	**-.52*****
Attractive		.48***
Outdoors		.48***
Smiling		.43**
Pertaining to sports/fitness		.39**
Followers		.35*
Candid		.31*
Dominant facial expression		.30*
Profile picture anonymity		.28*
Movies/TV		-.30*
Neutral face		-.32*
Inanimate objects		-.45**
Imbedded text		-.51***
Crowds	.30*	
Pertaining to academics	-.28*	
Videos	-.29*	

Note. Values in bold are statistically significant in the same direction for both validity and utilization.
***$p < .001$, **$p < .01$, *$p < .05$.

Table 12

Cues to Agreeableness on Instagram

	Valid *r*	Utilized *r*
Neutral facial expression	**-.39****	**-.46*****
Smiling		.44**
Positive facial expression		.41**
Absent Bio		.40**
Neat		.30*
Perceived age		.30*
Username anonymity		-.30*
Negative facial expression		-.32*
Links to other SNSs		-.33*
Dominant facial expression		-.33*
Inanimate objects		-.37**
Music		-.38**
Swear words		-.47***
Images of self with others	.35*	
Selfies	.30*	

Note. Values in bold are statistically significant in the same direction for both validity and utilization.
***$p < .001$, **$p < .01$, *$p < .05$.

Table 13

Cues to Conscientiousness on Instagram

	Valid *r*	Utilized *r*
Videos	**-.30***	**-.29***
Smiling		.59***
Positive facial expression		.57***
Neat		.56***
Attractive		.39**
Stylish		.35*
Outdoors		.35*
Posed		.34*
Bio Absence		.33*
Images of self with others		.31*
Religion		.29*
Unique others		.29*
Anonymity in profile picture		.28*

Imbedded text		-.30*
Art		-.33*
Music		-.34*
Swear words		-.36**
Images without people		-.40**
Username anonymity		-.41**
Inanimate objects		-.42**
Neutral facial expression		-.56***

Note. Values in bold are statistically significant in the same direction for both validity and utilization.
****p* < .001, ***p* < .01, **p* < .05.

Table 14

Cues to Negative emotionality on Instagram

	Valid *r*	Utilized *r*
Imbedded text		.44**
Neutral facial expression		.41**
Bio word count		.37**
Swear words		.35*
Images without people		.33*
Negative facial expression		.32*
Music		.29*
Movies/TV		.29*
Inanimate objects		.29*
Bio Absence		-.28*
Attractive		-.29*
Images of self with others		-.30*
Sports/fitness		-.31*
Candid		-.34*
Profile picture anonymity		-.36**
Neat		-.36**
Positive facial expression		-.46***
Smiling		-.50***
Outdoors		-.55***
Videos	.40**	

Note. ****p* < .001, ***p* < .01, **p* < .05.

Table 15

Cues to Open-mindedness on Instagram

	Valid *r*	Utilized *r*
Music	-.29*	.30*
Movies/TV		.29*
Perceived age		.29*
Politics		.29*
Bio emoji count		-.29*
Story highlights		-.30*
Multiple posts		-.32*
Images of self with others		-.44**
Presence of name	-.32*	

Note. ****p* < .001, ***p* < .01, **p* < .05.

Table 16

Cues to Extraversion on Twitter

	Valid *r*	Utilized *r*
Achievement		.49***
Candid		.45***
Gratitude		.43**
Bio word count		.36*
Images in posts		.34*
RT/10-100		.33*
Dominant facial expression		.33*
RT/Under 10		.32*
Birthday		.32*
Diverse others in photos		.32*
Pertaining to sports		.32*
Swear words		-.31*
Negativity		-.31*
Personalness of Bio		-.34*
Sadness		-.35*
Stress/Anxiety		-.41**
Smiling	.33*	
Selfies	-.34*	

Note. RT refers to the number of times retweeted tweets (nonoriginal posts) had been retweeted, with lower numbers indicating users reposting less popular or viral content. ****p* < .001, ***p* < .01, **p* < .05.

Table 17

Cues to Agreeableness on Twitter

	Valid *r*	Utilized *r*
Positivity		.65***
Positive facial expression	-.34*	.54***
Smiling	-.34*	.53***
Achievement		.51***
Diverse others in photos		.51***
Images of self with others		.49***
Optimism		.45**
Pertaining to sports		.45**
Gratitude		.36*
Video posts		.34*
Attractive		.34*
Stylish		.34*
RT/10-100		.34*
Followers		.33*
Following		.31*
RT/Under 10		.30*
Retweets		.30*
Sexual content		-.31*
Original tweets		-.31*
Sarcasm		-.31*
Initialisms		-.38**
Swear words		-.41**
Neutral facial expression		-.41***
Negativity		-.45***
Negative facial expression		-.50***
Anger		-.54***
Sexually explicit words	.33**	
Username anonymity (name)	.32*	
Pinned tweet	-.36*	

Note. RT refers to the number of times retweeted tweets (nonoriginal posts) had been retweeted, with lower numbers indicating users reposting less popular or viral content.
***$p < .001$, **$p < .01$, *$p < .05$.

Table 18

Cues to Conscientiousness on Twitter

	Valid *r*	Utilized *r*
Achievement		.50***
Positive facial expression		.49**
Smiling		.46**
Positivity		.44**
Gratitude		.39**
Diverse others in photos		.38**
Pertaining to sports		.38*
RT/10-100		.35*
Images of self with others		.34*
Political content		.34*
Following		.34*
Negativity		-.30*
Anonymity in Bio		-.30*
Pertaining to music		-.32*
Emojis		-.35*
Exaggerated/slang spellings		-.38*
Sexually explicit words	.35**	-.38**
User's name specificity		-.46***
Initialisms		-.52***
Swear words	.30*	-.54***
Mentions of generic others	.32**	
Sexual content	.36**	
Dominant facial expression	.31*	
Pertaining to other hobbies/interests	-.36**	

Note. RT refers to the number of times retweeted tweets (nonoriginal posts) had been retweeted, with lower numbers indicating users reposting less popular or viral content.
***p < .001, **p < .01, *p < .05.

Table 19

Cues to Negative emotionality on Twitter

	Valid *r*	Utilized *r*
Initialisms		.52***
Negativity		.49***
Swear words	-.36*	.49***
Sadness		.47***

Stress/Anxiety		.41**
Anonymity in Bio		.39**
Username anonymity (name)		.38*
User's name specificity		.32*
Personalness in Bio		.31*
Exaggerated/slang spelling		.30*
Following		-.30*
Optimism	.34*	-.31*
Video posts		-.33*
Images of only others (known)		-.33*
Images of self with others		-.37*
RT/10-100		-.39*
Pertaining to sports		-.40**
Smiling		-.41**
Diverse others in photos		-.44**
Candid		-.44**
Positive facial expression		-.45**
Positivity		-.46***
RT/Under 10		-.46***
Gratitude	.33*	-.48***
Achievement	.36**	-.61***
Bio word count	.38**	
Pertaining to art	.33*	
Religious content	.32**	
RT/10k-100k	-.35*	

Note. RT refers to the number of times retweeted tweets (nonoriginal posts) had been retweeted, with lower numbers indicating users reposting less popular or viral content.
***$p < .001$, **$p < .01$, *$p < .05$.

Table 20

Cues to Open-mindedness on Twitter

	Valid *r*	Utilized *r*
Images without people		.47***
Bio word count		.38**
Months on Twitter		.33*
Tweets		.33*
Pertaining to movies/TV		.32*
Bio emojis		.31*
Posed		-.30*
Dominant facial expression		-.34*
Neutral facial expression		-.34*

Swear words		-.36*
Negative facial expression		-.39*
Images in posts	.33*	
Sexual content	-.30*	
Initialisms	-.30*	
Pertaining to romantic relationships	-.33*	

Note. RT refers to the number of times retweeted tweets (nonoriginal posts) had been retweeted, with lower numbers indicating users reposting less popular or viral content.
***$p < .001$, **$p < .01$, *$p < .05$.

Overall, Twitter provided for more valid and utilized cues (valid = 25, utilized = 98) than Instagram (valid = 15, utilized = 78). However, considering that Twitter profiles were coded for 83 total cues and Instagram profiles were coded for 53 cues, the proportions of valid or utilized cues to total cues across traits is similar between profiles. On Instagram, 5.6% of cues coded (across all five traits) were valid, compared to 6% on Twitter. On Instagram, 29% of cues coded across traits were utilized, compared to 24% on Twitter. However, while there were 7 significant valid and utilized cues on Instagram across traits, there were none on Twitter. Again, this could help to explain differences in accuracy between the platforms.

Chapter 5: Study 1 Discussion

The goals of Study 1 were 1) to code the content on the collected social media profiles in order to better understand the cues being used to make accurate judgements, 2) to evaluate the hypothesis that higher anonymity on Twitter contributed to lower levels of judgement accuracy in comparison to Instagram, and 3) to identify cues that could be used to train judges to make more accurate perceptions using Twitter or Instagram profiles.

Regarding the first goal, utilizing both a principal components analysis and basic correlational approach to lens modeling revealed a couple of consistent patterns. First, across Instagram and Twitter, there were a greater number of utilized cues compared to valid cues. This suggests that judges utilized a wide range of the information available to them in forming their perceptions of targets' personalities of the Big Five traits. However, the relatively few valid cues could indicate that many of the behaviors displayed on social media are not directly related to specific personality traits, at least at the trait level of personality measured by the BFI-2 and at the level of coding utilized in this study. It is possible that more relationships between coded cues and personality would emerge if personality was examined in more detail at the facet level, which is not recommended for a sample this size when using the BFI-2-S (Soto & John, 2017). Additionally, while this coding scheme aimed to capture a wide range of available information, it is possible that important valid and/or utilized cues were not included in the coding scheme. Secondly, while utilized cues often made intuitive sense (e.g., pictures with others for extraversion, pertaining to music for open-mindedness), valid cues were often surprising. For example, on Instagram profiles, more posts pertaining to music was found to be a utilized cue to higher levels of open-mindedness while it was actually a valid cue to lower levels of open-mindedness. While this was the only instance of a cue being significantly utilized in the opposite direction from which it was significantly valid on Instagram, this pattern was more common on Twitter. For the trait of agreeableness on Twitter, utilized cues of smiling and positive facial expression for higher levels of agreeableness were actually valid cues for lower levels of agreeableness. For conscientiousness on Twitter, utilized cues of sexually explicit words and swear words for lower levels of conscientiousness were actually valid cues for higher conscientiousness. And for negative emotionality on Twitter, themes of achievement, optimism, and gratitude were all utilized as cues for lower levels of negative emotionality and were actually valid cues indicating higher levels of negative emotionality. This pattern of cues being utilized by judges in the opposite direction of their actual validity could contribute to the overall lower levels of accuracy on Twitter.

Relatedly, while seven cues (analyzed with basic correlations) across traits on Instagram were utilized and valid, leading to accurate judgements via the Lens Model framework, no valid and utilized cues existed on Twitter. This is not because there were fewer valid cues available compared to Instagram; Twitter had 27 valid cues across traits while Instagram had 15. Nor is this due to judges generally utilizing fewer cues; Twitter had 102 utilized cues while Instagram had 78. It seems to be the case that lower levels of accuracy were primarily due to judges paying attention to the wrong information and utilizing the wrong cues for traits. Why judges may be paying attention to the wrong cues to a greater extent on Twitter compared to Instagram is unclear. It is possible that the issue lies on the side of the judge. Perhaps the greater density of information presented on Twitter profiles is overwhelming and distracting, while Instagram provides for a simpler visual processing task. It is also possible that, given the amount of information and the relatively more taxing task of reading (as opposed to viewing pictures), judges may not have been putting the same amount of effort into forming impressions of targets based on Twitter profiles. Judges completed the survey outside the lab, on their own devices and via online recruitment, so there is no way to know if equal effort was made by judge participants across SNS platform type. A minimum viewing time of 10 seconds per profile was enforced to help ensure some consistency, however, especially for Twitter profiles, this was likely not enough time to fully examine the profiles. Alternatively, the issue could also be on the side of the target. While past analyses did not find any significant differences between Instagram and Twitter targets in terms of the BFI-2, it is possible that some other difference exists between the types of people who are active on Instagram versus Twitter that could have led to Twitter users behaving in ways that would not typically be considered in-line with their personalities, thus resulting in the pattern of surprising valid cues. The idea that Twitter users might behave in unexpected and potentially inauthentic ways is partially what led to the development of Hypothesis 1.

Higher levels of anonymity have sometimes been found to be related to more inauthentic behavior online. Hypothesis 1 posited that differences in accurate judgements between Twitter and Instagram could be explained by higher levels of anonymity on Twitter. However, at least when measuring anonymity using the composite anonymity score outlined in the Method section, there was not a significant difference in anonymity between Instagram and Twitter profiles. When examining the components of the accuracy score individually, the only significant differences were in the opposite direction as hypothesized, with Instagram being more anonymized than Twitter on two cues. While the presence of more specific location information on Twitter can be explained by Twitter's prompting users to provide this information in their bio, the usage of more identifying usernames on Twitter (featuring the user's full first and last name) was surprising. One limitation to consider is that these profiles were collected primarily using the university recruitment pool. Any profile information provided by participants was within the context of an academic study, so it is unlikely that the more extremely anonymized profiles were collected. Another thing to consider is that perhaps anonymity, in terms of being able to locate/identify a person based on their profile, is less important for accuracy than a profile's connection to the offline social circles of the profile owners. Perhaps whether or not it is possible to find one's profile is less related to authenticity of behavior than whether the people one knows offline are actually watching them online. Connection to offline social circles could be hypothesized as a moderator of accuracy using much of the same reasoning that led to the hypothesis of anonymity as a moderator of accuracy. In order to assess this, it would be necessary to identify the proportion of followers on a profile that are also offline friends, which is not possible with the current data but could be an interesting avenue for future research.

Despite nonsignificant differences between profile types, when anonymity was used as a moderator in the SAM, anonymity did moderate normativity, with more anonymous profiles being judged with lower levels of normativity, but this was only true on Twitter profiles. This suggests that judges on Twitter are perceiving something different about targets who present more anonymously online, to the detriment of accurate judgements. Targets who present more anonymously on Twitter are being inaccurately perceived as less similar to the average person. Given that the average personality also tends to be positive (e.g., Rogers & Biesanz, 2015), it is possible that more anonymized targets are also being perceived less positively. This has potential implications for Twitter users who prefer to remain more anonymous, as the tradeoff may be being perceived by others in a less positive light.

The last goal of Study 1 was to identify cues to use in training for Study 2. Using principal component analysis, the groups of cues that formed components tended to lack face validity in terms of their interconnectedness, which would likely make training more difficult or confusing for participants. For this reason, cues were identified using basic zero-order correlational analysis. Similar to the findings of the basic correlational analysis, however, Instagram had one component that was valid and utilized, while Twitter had none. On Twitter, the two traits that had related valid components were conscientiousness and open-mindedness, which were also the two traits selected for training. Although the specific cues for use in training were selected using basic correlational analysis, the components had some cues in common with those identified in correlational analysis, as would be expected. Perhaps more interesting are the cues within components that were not identified as significant by correlational analyses. For example, one component that was valid for the trait of conscientiousness on Twitter contained the cue of "mentions of generic groups of others" which was one of the cues identified as valid by correlational analysis. Also included in this component were cues of anger and pertaining to politics. The relationship between this group of cues and valid ratings of conscientiousness could potentially be driven by a few particularly politically-conscious targets, arguing/debating political topics (hence ratings of anger) and referring to groups of other people in referencing political parties, for example. This was one of the few principal components that contained cues that could be logically connected, however, exploring these components further, and determining the extent to which they replicate in other Twitter profiles both in terms of content and trait validity/utilization, could provide interesting avenues for future research.

Limitations

The extent to which the cues identified through basic correlational analysis also replicate outside of the analyzed profiles is unclear. Again, while none of the self-report measures indicated that the targets who provided Twitter profiles differ in any meaningful ways from

Instagram targets, it is possible that this group is a unique subset of the population, and their behaviors may not provide for generalizable valid cues. Additionally, the online environment of Twitter has changed drastically since these profiles were collected. The acquisition of Twitter by Elon Musk in 2022 prompted many algorithmic and content/stylistic changes that has prompted many users to leave the site or alter the way in which they use Twitter. With these changes, beyond the expected changes in content, the behaviors of and perceptions of active Twitter users in the year 2023 may be different than the behaviors and perceptions captured in 2020. Overall, the cues identified as valid in these analyses, while adequate for training and testing on the same profiles, and for evaluating the efficacy of the training process, as is the goal of Study 2, likely lack externalizable generalizability today.

Chapter 6: Study 2 Literature Review

Training and Improving Accuracy

Due in part to the associations between accurate personality judgement and a variety of beneficial interpersonal outcomes, there has been much research on the topic of training and improving person perception, especially within the contexts of the workplace. However, research specific to training and improving accurate trait judgements is relatively sparse. Meta-analytic research on improving person perception accuracy found that practice with feedback about performance was the most effective training method for improving accurate judgements (Blanch-Hartigan & Cummings, 2021). It did not seem to matter whether the feedback was specific (i.e., the correct answer was given after each item) or general (i.e., given at the end, pertaining to overall performance). Simply instructing judges on which cues to look for was not effective. Motivating judges to be more accurate is similarly ineffective. One study, examining 11 experiments and using five different methods of motivation, found that motivating participants to be more accurate on an interpersonal sensitivity test to nonverbal cues did not improve accuracy (Hall et al., 2009). One way to conceptualize the training and improving of accuracy is to return to the Realistic Accuracy Model (Funder, 1995) and focus on each of the four steps to improve accuracy from the perspective of the judge (Blanch-Hartigan & Cummings, 2021; Letzring & Funder, 2021).

Relevance

Beginning with step one, relevance requires some sort of cue that is relevant to the target's personality. This stage, along with availability, is considered to primarily be under the control of the target. However, taking the perspective of the judge, it may be useful for a judge to understand the constraints or context of a given situation or environment and how these could influence target behavior. Some situations are “stronger” than others, meaning that most individuals in a strong situation will behave similarly, and individual differences may be less apparent (Ickes et al., 1997). In a weaker situation, individuals may express themselves more openly due to less situational constraints, and thus display more relevant cues about their personality. However, certain situations can also be more useful than others when looking for relevant trait-specific cues. For example, negative emotionality, which can be very difficult to judge accurately in first-impressions (e.g., Funder, 2012; Kenny & West, 2008; Vazire, 2010) can be judged with higher levels of accuracy when targets are observed in a situation that is more relevant to the trait of negative emotionality, such as a consequential introductory situation where the targets know they will be subsequently evaluated on their likability by others (Hirschmüller et al., 2015). Additionally, Hirschmüller et al. (2015) identified a number of valid and utilized cues from these situations, including visual cues (e.g., nervousness of facial expression, timidness of facial expression, nervousness of bodily behavior, withdrawn behavior) and vocal cues (e.g., nervousness of voice, low volume of voice, weakness of voice, speech disfluency). These aggregate groups of cues were found to be valid and accuracy was indeed mediated by the utilization of these cues.

Conceptualizing social media platforms as their own unique environments, it is possible that Instagram and Twitter vary in the strength of the situations provided on each platform. Additionally, one platform may provide for more trait-relevant cues than another platform due to the nature of the online environment in the same way that in-person environments and situations influence the relevancy of cues that are displayed. Explaining these differences in the online environments, if they exist, could be an essential piece in training a judge to improve accurate judgement online.

Availability

The second step in RAM is availability, which is defined by the necessity of cues being visible/observable for the judge. The best way to improve availability of trait-relevant cues may be by increasing the quantity of information (Blanch-Hartigan & Cummings, 2021). In this way, by increasing the number (and variety) of situations in which a target is observed, judges can observe the available cues in each individual situation and aggregate observations to form more accurate judgements. Again, considering the context of social media profiles, a larger quantity of posts/activity is likely better for forming accurate judgements. Some users post more infrequently, perhaps sharing only significant occasions/milestones or otherwise “important” personal information, or simply more sporadic coverage of their thoughts, feelings, and behaviors. The more frequently a user posts, the more likely they are sharing daily aspects of their life, more minor details of their regular behaviors, thoughts, and feelings, and thus providing more cues over time. In addition to frequency, the type or quality of the information being shared should also be considered, specifically in terms of variety. If an individual only posts “highlights” of their lives, such as relatively infrequent celebratory moments or exciting/unusual experiences, judges will not have as much information as with targets that post about these things in addition to boring daily activities, or even low points in life. The greater the variety of real-life behaviors, thoughts, feelings, and situations that are being made available on social media, the more accurate a judge is likely to be. Judges could therefore be trained to look for variety of posts as well as frequency.

Detection & Utilization

While relevance and availability are more under the control of the target, the judge has more agency at the detection and utilization stages. In these stages, judges must be attentive and perceptive in order to detect cues and be correct in their understanding of the relationships between those cues and personality in order to relate their observations back to the relevant traits. This is where lens models can be used to examine which cues judges use when judging particular traits and how those cues actually relate to the personality of the targets (e.g., Back & Nestler, 2016; Nestler & Back, 2013). Using cues identified by lens models, judges can be trained to direct their attention towards cues that are valid for specific traits, and away from invalid cues, increasing both detection and utilization. Within the present study, these are the stages of RAM that will be the main focus of trainings.

Study 2 Hypotheses

Study 2 consisted of a more traditional experimental design, testing three conditions, which will be explained thoroughly in the Method section. It was hypothesized that the experimental group that received cue validity and utilization training as well as personalized feedback regarding their personality judgements, would have higher levels of accuracy than the experimental group that received only cue validity/utilization training. In turn, it was hypothesized that the experimental group that received only training would have higher levels of accuracy than the control group, which would receive no training or feedback.

Chapter 7: Study 2 Method

The goal of Study 2 was to compare two types of automated training to improve judgement accuracy, while also collecting perceptions from judges who received no training as a control group. Specific methodology design decisions relied heavily on the results of Study 1, which were presented in Chapter 4.

Selection of Traits and Profiles

As the focus of Study 2 is the process of training and improving accuracy using cues, only Twitter profiles were utilized as stimuli. Twitter profiles were chosen over Instagram for a few reasons. First, within my thesis, overall accuracy on Twitter was lower, providing more room for improvement. Second, as expected due to the volume of content, Twitter profiles were found to broadly provide for more valid and unutilized cues, providing more options for training on cues that were related to target self-reports but were not being used by judges. In order to test the efficacy of training, the personality traits of Open-mindedness and Conscientiousness were used because they exhibited valid, unutilized cues and were rated with nonsignificant levels of distinctive accuracy within my thesis, indicating substantial room for improvement in accuracy. Four valid unutilized cues for each trait were chosen as the focus for training. Twelve Twitter profiles were selected that best exemplified the traits and cues of interest. This was done by examining profiles in the upper and lower quartiles for each trait of interest, and choosing profiles that had the most (or least, depending on trait level) instances of relevant cue expression. Four profiles for each category (Low Open-mindedness, High Open-mindedness, Low Conscientiousness, High Conscientiousness) were selected, without repetition. A few profiles that were identified as being Format Type 2 (mobile version), and which were slightly visually different than the majority of profiles (web version) were not used to ensure maximum consistency across stimuli. Additionally, three profiles were selected to use for training. These profiles had levels for both traits of interest that were within the upper or lower quartile, and at least some of the relevant cues for each trait. On average, the personality traits of the 12 targets chosen did not differ in any significant ways from Soto's (2019) representative United States sample, and are described in Table 21.

Table 21

Chosen Target Personality

	Mean (SD)	95% CI	Range	Skewness	Kurtosis	*t* (11)	*d*
Extraversion	3.29 (0.41)	3.06 – 3.53	2.5-4.17	0.17	1.54	.63	.18
Agreeableness	3.81 (0.75)	3.38 – 4.23	2.33-4.83	-0.43	-0.46	-.05	.02
Conscientiousness	3.79 (0.59)	3.46 – 4.13	2.03-4.67	0.12	-1.08	-.55	.16
Negative Emotionality	2.71 (1.01)	2.14 – 3.28	1-4.17	-0.161	-1.07	-.04	.01
Open-mindedness	3.54 (0.82)	3.08 – 4.01	2.16-5	-0.18	-0.46	-.05	.13

Note. t-test results are one-sample *t*-tests comparing Soto's (2019) representative US sample to the 12 chosen targets.

Judge Participants

Participants consisted of 150 judges ranging in age from 18-71 (M = 34.13, SD = 10.86) recruited through CloudResearch Connect. Judges were put into one of three conditions, which will be described in a later section. Within multilevel modeling, a sample size at level 2 of at least 50 has been found to provide for regression coefficients, standard errors, and variance estimates that are unbiased and of acceptable reliability (Maas & Hox, 2005). So, each condition group will consist of 50 judges with the final sample size totaling 150.

All demographics were collected through open response text-entry questions and recoded for analysis. Gender was made up of 51.33% male and 48.67% female. Race/Ethnicity (using language used by participants themselves) was 60% White/Caucasian, 11.33% Black/African American, 11.33% Asian/Asian American, 9.33% Hispanic/Latinx, 5.33% identified as multiple races/ethnicities, 1.33% Native American, and 1.33% participants identified only as "American".

Measures

Personality

Personality traits were measured using the 30-item BFI-2-S (Soto & John, 2017). Judges completed a self-report of this measure, as well as an other-report version for each target. Good internal reliability was found for each trait within this study (α = .75 - .89).

SNS Use Frequency

Judges were asked two single-item questions pertaining to the frequency of their use of social networking sites in general and Twitter specifically, respectively. These questions were based on the Pew Research Center Annual Social Media Use Report (Pew Research Center, 2022) and asked "How often do you use social media? (e.g., Facebook, Instagram, Twitter, LinkedIn, Snapchat, WhatsApp, others)?" and "How often do you use Twitter?" on a five-point response scale ranging from "Less than every few weeks" to "Multiple times per day."

Confidence in Accurate Judgements

After judges completed their perception ratings of all targets, they were asked four questions about their confidence in the accuracy of their judgements on a five-point response scale ranging from "Very confident" to "Not at all confident." First, they were asked "How confident are you that your overall impressions of personality were accurate?" Then they were told to imagine three different scenarios and asked "How confident are you that viewing these Twitter profiles would help you make the right decision?" The three scenarios were 1) Imagine you are in charge of hiring and these were the Twitter profiles of job candidates, 2) Imagine you are looking to make new friends and these were the Twitter profiles of potential friends, and 3) Imagine you are looking for a romantic partner and these were the Twitter profiles of potential dates.

Demographics

Judge participants were asked to answer free-response text-entry questions providing their age, gender, and race/ethnicity.

Procedure

Participants completed the self-report BFI2-S, and SNS use frequency questions first. After this, participants were randomly placed[2] into one of three conditions, described in the following sections. Due to the risks associated with using online data collection services, many attention checks, bot and fraud detection methods were utilized. For example, passing a simple quiz about the study itself (with the correct information presented in the same page) was required to begin the main study. In addition to a reCAPTCHA, and attention checks in each BFI (self- and other-report) measure, checks in the form of specific and unique multiple-choice questions

---

[2] Because the control condition took much less time to complete (15-25 minutes) than the other two conditions, two separate CloudResearch Connect listings were created in order to pay participants the same hourly rate between all conditions. When participants began one study (either the Control or the Training/Training and Feedback, which shared a single Cloud Research Connect listing) they were immediately disqualified from viewing or participating in the other. Which listing a individual participant came across first depended on the individual's sorting/search preferences. Sorting by total pay would list the experimental conditions higher, while sorting by lower time commitment would list the control condition higher. Both listings were started by participants at roughly the same rate, although the experimental conditions had a higher drop-out/bounce back rate, likely due to the more involved procedure. Participants were truly randomized between the Training Only and Training and Feedback conditions through Qualtrics randomization.

about the content of each profile were presented after each profile. If a participant missed 5 (more than 20%) attention checks, they were directed out of the study after completing the given question block. After the first three profiles, participants saw a screen that told them how many attention checks they had done correctly so far out of seven, and were reminded that if they missed more than 20% at any point, they would be unable to complete the study. This was also the first time that participants attention check score was evaluated and participants could be redirected out of the survey if they had failed 5 or more attention checks. Across conditions, 8.2% of participants who started the study did not complete the study due to failed attention checks. 32.9% of participants who started the study did not finish the study for other reasons. Some feedback on CloudResearch Connect from these unfinished participants included “Not worth the money”, “Too tedious”, and “Thought I had time but had to go.” Overall, 58.9% of participants who clicked into the study on CloudResearch Connect successfully completed the study and received payment at a rate of $6 per hour i.e., $4.50 for the control group, $6 for the other two conditions.

Training Only Group

One group of 50 judges received personality judgement accuracy training consisting of information about how specific cues are utilized and valid on Twitter profiles relating to the traits of Conscientiousness and Open-mindedness. This training consisted of a recorded presentation (transcript provided in Appendix C) providing information about each trait, the cues that relate to each trait, and examples of cues, as shown on Twitter profiles that they will not be rating, some of which were artificially generated to provide examples. The final part of training was a manipulation check consisting of a short quiz about the cues relevant to the traits of interest. This quiz consisted of two multiple-choice questions that asked participants to identify the cues for each trait (one trait per question). The multiple-choice options consisted of all eight trained cues plus two distraction cues. Participants who did not answer this manipulation check correctly were reshown the summary from the end of the training video (a "cheat sheet" list of cues for both Conscientiousness and Open-mindedness) and then asked to try the quiz again, on a separate page from the cheat sheet. If failed a second time, a warning appeared that they needed to answer the questions correctly or risk being removed from the study. Participants were told exactly which cues they incorrectly identified and what the correct classification is, and the quiz was presented again, with the cheat sheet presented on the same page. If failed a third time, participants were redirected out of the study and assumed to be bots/invalid responses. After this training, participants rated the owners of nine social media profiles using the BFI-2-S. Only the last six profiles were used to calculate accuracy. Following the third and sixth profiles, participants were reminded of the information they received in training in the form of a list of cues and their relationship to the traits of interest. The manipulation check was also repeated, with an identical approach to handling incorrect responses to the first time. This was an effort to strengthen the manipulation by ensuring that participants paid attention and remembered the training throughout the study. 84.7% of participants in this group who made it past the first three profiles also successfully passed the remaining necessary attention checks and completed the study, with an average completion time for 59 minutes and 7 seconds.

Training and Feedback Group

The next group of 50 judges received the same training as the Training Only Group. However, after rating each owner of the first three profiles, participants received automated feedback consisting of their rating of trait-relevant items alongside the target's actual self-report, and asked participants to compare how the two ratings. Cues specific to the trait were highlighted during this feedback (see Figure 5). After presentation of feedback, participants responded to a multiple-choice question to compare their rating of the trait to the actual rating. Two free-response questions were also asked that prompted judges to reflect on the cues they used while making their judgements, and whether or not these are cues they were trained to use (see Figure 6). After completing the first three profiles, participants were reminded of the information they received in training using the same "cheat sheet" list of cue relationships presented to the Training Only Group and completed the manipulation check quiz. This list and quiz were also displayed after the sixth profile. Only the last six profiles rated were used to calculate accuracy. Participants did not receive feedback while rating these final six profiles. 83.33% of participants in this group who made it self-report portion and the first three profiles also successfully passed the necessary remaining attention checks and completed the study, with an average completion time of 63 minutes and 3 seconds.

Figure 5

Example of Feedback

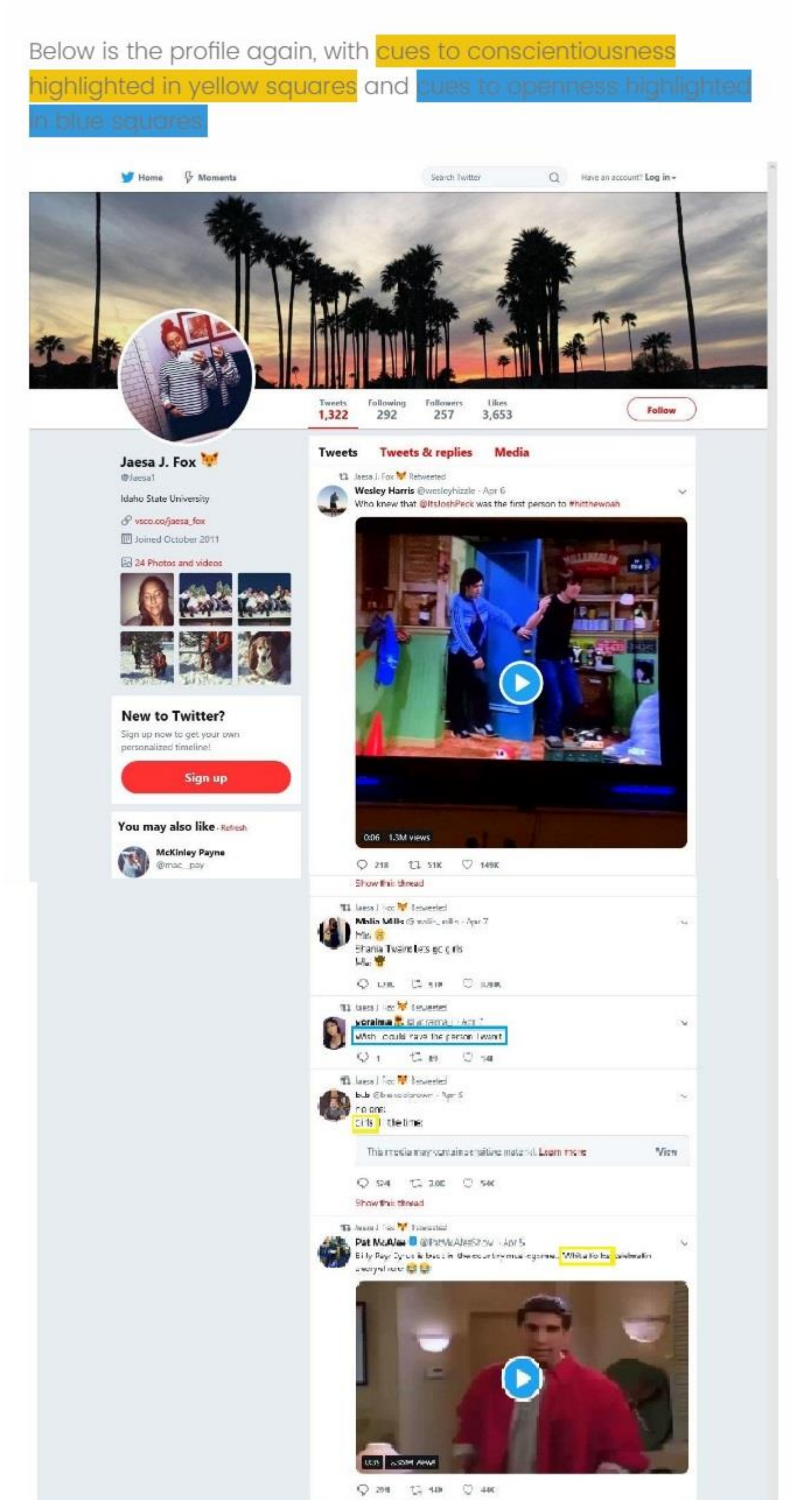


Figure 6

Post-feedback Questions

You rated this person's conscientiousness as 3.6666666666666665 on a 1-5 scale.

This person's actual conscientiousness is 2.667 on a 1-5 scale.

Compared to this person's actual conscientiousness your rating was...

- ○ Too low
- ○ Exactly right
- ○ Too high

You rated this person's openness as 2.8333333333333335 on a 1-5 scale.

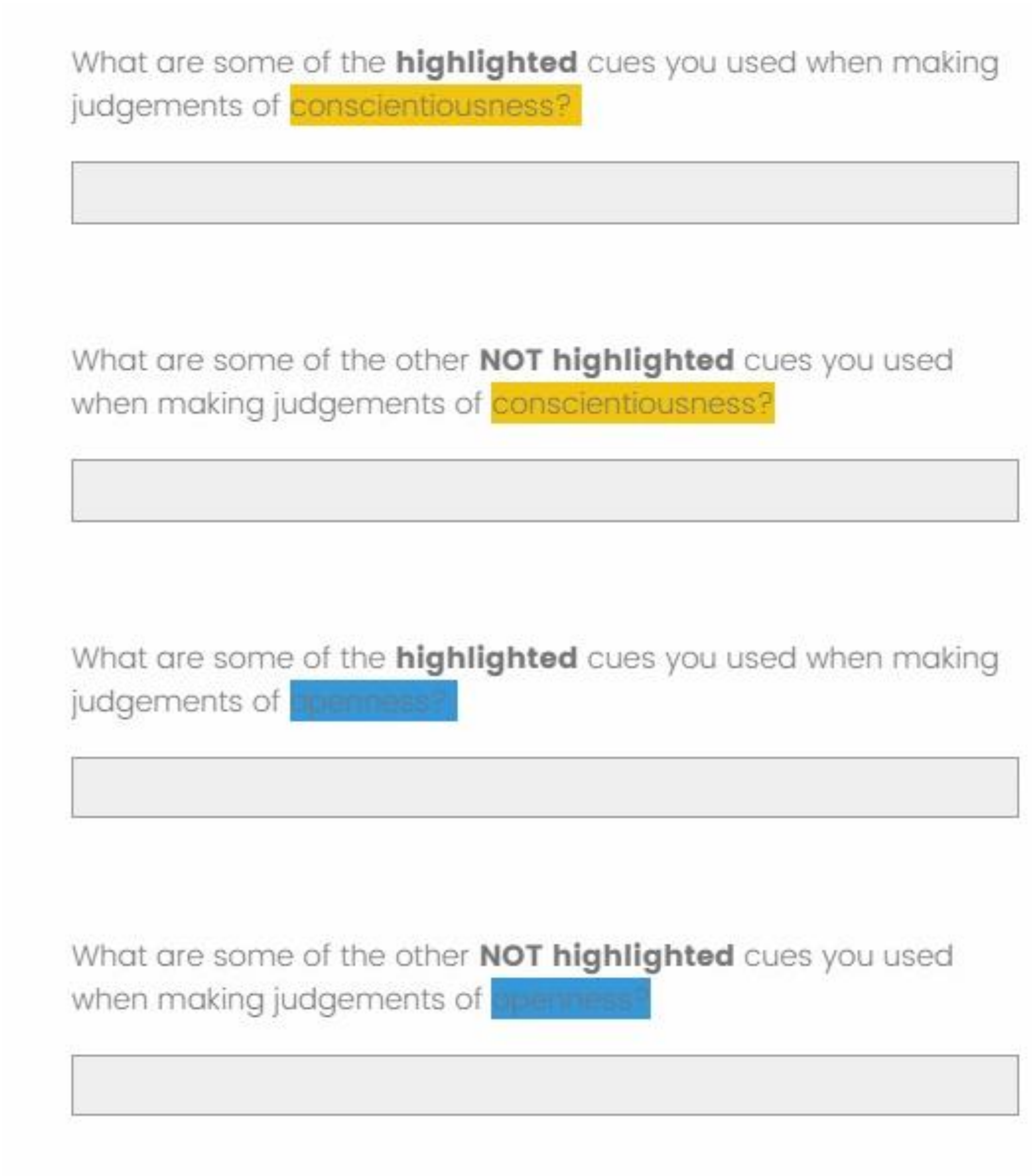
This person's actual openness is 4.25 on a 1-5 scale.

Compared to this person's actual openness your rating was...

- ○ Too low
- ○ Exactly right
- ○ Too high

Figure 6 (cont.)

Post Feedback Questions



What are some of the **highlighted** cues you used when making judgements of conscientiousness?

What are some of the other **NOT highlighted** cues you used when making judgements of conscientiousness?

What are some of the **highlighted** cues you used when making judgements of openness?

What are some of the other **NOT highlighted** cues you used when making judgements of openness?

Control Group

The final group of 50 judges serves as a control condition by providing personality ratings for nine targets without any training or feedback. Only the last six profiles were used to calculate accuracy. 90.9% of participants who made it past the first three profiles also passed the necessary attention checks and completed the study, with an average completion time of 36 minutes and 21 seconds.

Analysis

The Social Accuracy Model (SAM) is a multilevel model designed specifically for use in judgment accuracy research. SAM uses a hierarchical linear model design to simultaneously examine normativity and distinctive accuracy. Within this study, the normative profile was calculated as the average for each item of the BFI-2, across all targets from my thesis. The normative and distinctive profiles were grand-mean centered. This allows for accuracy estimates to be more easily interpreted, with either distinctive accuracy or normativity being at their respective average level while the other is held at 0, which is the average. The SAM uses the following regression equations:

$$Y_{jti} = \beta_{0jt} + \beta_{1jt}\ TCrit_{ti} + \beta_{2jt}\ Mean_i + \varepsilon_{jti} \qquad (1.1)$$

$$\beta_{0jt} = \gamma_{00} + u_{0j} + u_{0t} \qquad (1.2)$$

$$\beta_{1jt} = \gamma_{10} + u_{1j} + u_{1t}$$

$$\beta_{2jt} = \gamma_{20} + u_{2j} + u_{2t}.$$

In equation 1.1, Y_{jti} is judge *j*'s rating of target *t* on item *i*. $Tcrit_{ti}$ corresponds to target *t'*s accuracy criterion on item *i*. $Mean_i$ is the mean accuracy criterion on item *i,* which represents the average person's rating on item *i*. ε_{jti} represents the residual or error. In equation 1.2, β_{0jt} is the average intercept, and the average predicted value of judge *j*'s rating of target *t* on item *i* when $Tcrit_{ti}$ and $Mean_i$ are held constant at the average, which is 0 due to mean centering. B_{1jt} is the predicted value for distinctive accuracy when $Mean_i$ is held constant at the average. B_{2jt} is the predicted value for normativity when $Tcrit_{ti}$ is held constant at the average. Γ_{00} represents the average intercept, while γ_{10} and γ_{20} represent the average distinctive accuracy and normativity slopes, respectively, across judges and targets. The *u*'s represent the residuals of the model for the judge (u_j), and the target (u_t). To calculate overall accuracy, across groups, a SAM equation without moderators was run that included all judges.

Characteristics of situations, targets, or judges can be added into the equations to examine how these variables moderate normativity and distinctive accuracy. In the present study, the condition or group to which judges were assigned is the moderator of interest. The hypothesis for the present study predicted that accuracy would be highest in the Training and Feedback (TF) group, followed by the Training Only (TO) group, with accuracy being the lowest in the Control (C) group. The following equations (2.1 and 2.2) represent how the dummy-coded groups variable (*grp*) were entered into SAM as a moderator.

$$Y_{jti} = \beta_{0jt} + \beta_{1jt}\, TCrit_{ti} + \beta_{2jt}\, \mathrm{Mean}_i + \varepsilon_{jti} \qquad (2.1)$$

$$\beta_{0jt} = \gamma_{00} + \gamma_{01} grpTO + \gamma_{02} grpTF + u_{0j} + u_{0t} \qquad (2.2)$$

$$\beta_{1jt} = \gamma_{10} + \gamma_{11} grpTO + \gamma_{12} grpTF + u_{1j} + u_{1t}$$

$$\beta_{2jt} = \gamma_{20} + \gamma_{21} grpTO + \gamma_{22} grpTF + u_{2j} + u_{2t}$$

In the equations above, the two dummy coded variables are *grpTO* (1=TO, 0=TF, 0=C) and *grpTF* (0=TO, 1=TF, 0=C). The Control (C) Group is the comparison group in this example and is coded as 0 in both variables. The interactions between the distinctive profile and the dummy coded variables will test whether distinctive accuracy is moderated by group, and the interaction between the normative profile and the dummy coded variables will test whether normativity is moderated by group. Analysis will examine accuracy for all traits combined as well as for individual traits.

Table 22

Dummy Coded Variables

	grpTO	grpTF
Training and Feedback Group	0	1
Training Only Group	1	0
Control Group	0	0

The following is the R code for testing whether distinctive accuracy and normativity are moderated by group.

```
> summary(TFcomparison.bfi2 <- lmer(Rating ~ 1 + Tcrit.MC*grpTO + Tcrit.MC*grpTF +
Norm.MC*grpTO + Norm.MC*grpTF + (1 + Tcrit.MC + Norm.MC | JudgeID) + (1 + Tcrit.MC
+ Norm.MC | TID), data = SAM.bfi2))
```

The term *lmer* is the linear mixed effect regression function. In this equation, *Rating* is the judge perception of a target on an item on the BFI-2 and is the dependent variable. The ~ is the operator that separates the dependent variable on the left side from the predictors and random effects on the right side. The number 1 is a placeholder for the intercept. Tcrit.MC is the mean-centered distinctive accuracy criterion (also referred to as the distinctive profile) and Norm.MC is the mean-centered normativity criterion (also referred to as the normative profile). This model examines whether Group (grpTO and grpTF) moderates distinctive accuracy and normativity. The term *(1 + Tcrit.MC + Norm.MC | JudgeID)* allows coefficients to vary by judge, while *(1 + Tcrit.MC + Norm.MC | TID)* allows coefficients to vary by target.

The output for the above analysis produced four relevant regression coefficients: Tcrit.MC:grpTO (difference in distinctive accuracy between TO and the other two groups), Tcrit.MC:grpTF (difference in distinctive accuracy between TF and the other two groups), grpTO:Norm.MC (difference in normativity between TO and the other two groups), grpTF:Norm.MC (difference in normativity between TF and the other two groups). It was predicted that there would be statistically significant positive regression coefficients for the comparisons of the Training and Feedback Group, indicating that the Training and Feedback Group has higher accuracy than the other two groups. This same analysis was done with the Training Only Group as the comparison group to compare the Control with the other two groups, with the prediction that regression coefficients would be negative, indicating lower accuracy in the Control Group than the other two groups.

Chapter 8: Study 2 Results

Judge's self-reported personality scores can be found in Table 23, and correlations for self-report variables can be found in Table 24. Notably, usings one sample t-tests to compare to Soto's 2019 representative US sample, the judges in this study had significantly lower levels of Extraversion, t (149) = -5.13, p < .001, with a difference in means of -.40, d = .42, 95% CI [-0.585, -0.252] and significantly higher levels of Open-mindedness t (149) = 5.121, p < .001, with a difference of .32, d = .42, 95% CI [0.251, 0.584].

Table 23

Judge Personality

	Mean (SD)	95% CI	Range	Skewness	Kurtosis
Extraversion	2.82 (0.95)	2.66 – 2.97	1-5	0.09	-0.61
Agreeableness	3.85 (0.77)	3.73 – 3.98	1.33-5	-0.43	-0.35
Conscientiousness	3.75 (0.91)	3.61 – 3.89	1.17-5	-0.42	-0.48
Negative Emotionality	2.76 (1.09)	2.58 – 2.93	1-5	0.07	-0.78
Open-mindedness	3.96 (0.74)	3.84 – 4.08	1.33-5	-0.65	0.38

Participants reported using social media generally at seemingly higher rates than Pew Research's 2021 sample of US adults, although direct comparison is not possible as Pew Research asks about individual sites, not general use. In the current study, 76% of participants report using social media several times per day, compared to Pew Research's finding that the most frequently used individual SNS was Facebook, with 49% of users visiting several times per day. Frequency of Twitter usage can be directly compared, as 40% of participants in this study used Twitter several times per day, compared to 30% of US adults. Statistical tests of the significance of this difference is not possible at the moment, as Pew Research has not responded to my request for the data. Neither general SNS use (F (2, 147) = 2.35, p = .099) nor Twitter use (F (2, 147) = 1.917, p = .151) differed significantly across conditions.

Table 24

Judge Variable Correlations

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Ext	-											
2. Agr	.35 ***	-										
3. Con	.42 ***	.44 ***	-									
4. Neg Emo	-.50 ***	-.49 ***	-.64 ***	-								
5. Open	.35 ***	.19 *	.23 **	-.19 *	-							
6. SNS Frequency	-.01	-.12	-.25 **	.18 *	.01	-						
7. TW Frequency	.07	-.01	.07	-.09	.10	.38 ***	-					
8. General Confidence	-.18 *	-.13	-.24 **	.30 ***	-.11	-.01	-.11	-				
9. Hiring Confidence	-.10	-.09	-.05	.21 **	.10	-.17 *	-.09	.52 ***	-			
10. Friendship Confidence	-.12	-.02	.17 *	.15	.08	-.12	-.09	.31 ***	.37 ***	-		
11. Dating Confidence	-.01	.13	.22 **	.02	.12	-.23 **	-.06	.22 ***	.44 ***	.56 ***	-	
12. Gender	-.11	.02	-.04	.24 **	.13	.08	-.19 *	.26 **	.27 ***	.09	.06	-
13. Age	.20 *	.18 *	.31 ***	-.24 **	-.02	-.13	-.01	.12	.02	.01	.14	.19

Note. *** p <.001, **p <.01, *p <.05. Gender was coded as 1 = Male, 2 = Female. Confidence was measured on a 1-5 scale.

Some personality traits significantly correlated with SNS use frequency and confidence in accurate judgements. More frequent general SNS use was related to lower conscientiousness (r = -.25, p < .001) and higher negative emotionality (r = .18, p <.05). General confidence in the accuracy of one's judgments was related to lower extraversion ($r = -.18$, $p < .05$), lower conscientiousness ($r = -.24$, $p < .01$), and higher negative emotionality ($r = .30$, $p < .005$). Confidence in one's judgements in relation to who to hire based on profiles was related to higher negative emotionality ($r = .21$, $p < .01$) as well as lower SNS usage ($r = -.17$, $p < .05$). Confidence about one's judgements in relation to who to be friends with based on profiles was related to higher conscientiousness ($r = .17$, $p < .05$), and confidence about one's judgements in relation to who to go on a date with based on profiles was also related to higher conscientiousness ($r = .22$, $p < .01$) as well as lower SNS usage ($r = -.23$, $p <.01$). Confidence in judgements generally, in relation to hiring, friendship, and dating by condition is presented in Table 25. A MANOVA revealed no significant differences between conditions in terms of confidence, F (2, 147) = 0.755, $p = .642$.

Table 25

Confidence in Judgements

	General Accuracy	Hiring	Friendship	Dating
	Means (*SD*)			
Control	2.28 (0.83)	2.82 (1.19)	1.96 (0.97)	2.38 (1.21)
Training Only	2.24 (0.94)	2.62 (1.24)	1.84 (0.86)	2.16(1.22)
Training and Feedback	2.54 (1.15)	2.94 (1.33)	2.22 (1.83)	2.62(1.35)

Analyzing accuracy across conditions, judges achieved statistically significant distinctive accuracy ($b = .108$, $SE = .048$, $p = .044$) and normativity ($b = .385$, $SE = .079$, $p < .001$) across traits. For individual traits across conditions, distinctive accuracy was not found for any trait. Normative accuracy, however, was significant for Conscientiousness ($b = .523$, $SE = .145$, $p =$

.003), Extraversion (*b* = 1.078, *SE* = .238, *p* < .001), and Negative emotionality (*b* = .640, *SE* = .136, *p* < .001).

Hypothesis 1

It was hypothesized that the experimental group that received training and feedback would have higher levels of accuracy than the experimental group that received only training. In turn, it was hypothesized that the experimental group that received only training would have higher levels of accuracy than the control group, which would receive no training or feedback. Analyzing accuracy using the experimental condition as a moderator as described in the analysis section, there were no significant differences between the groups. The training and feedback group did not differ significantly from the training only group and control group for distinctive accuracy (*b* = 0.02, *SE* = 0.023, *p* = .262) or normativity (*b* = 0.02, *SE* = 0.082, *p* = .768), nor did the control group differ significantly from the training and feedback group and training only group for distinctive accuracy (*b* = -0.01, *SE* = 0.023, *p* = .738) or normativity (*b* = 0.01, *SE* = 0.082, *p* = .974). All accuracy analysis results are presented in Table 26.

Looking at overall accuracy levels between conditions, depicted in Figure 5, the pattern of differences, although nonsignificant, is interesting to consider. Levels of distinctive accuracy were the same in the control group and training only group, but higher in the training and feedback group. Normativity on the other hand, is lowest for the training only group, followed by control, with the highest levels in the training and feedback group.

Table 26

All Accuracy Analysis Results

	Distinctive Accuracy		Normativity	
All Traits	B	SE	B	SE
Across Conditions	.108*	.048	.385***	.079

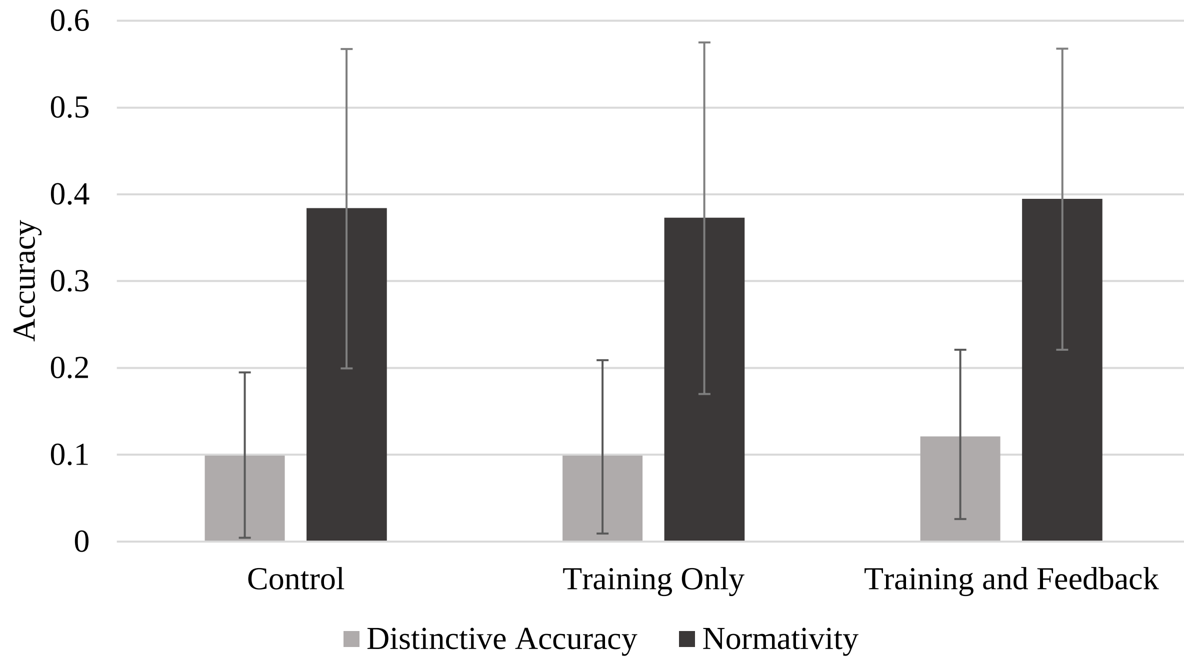
Training and Feedback	.121*	.049	.403***	.093
Training Only	.107*	.049	.375***	.093
Control	.095	.049	.377***	.093
C v TO	.013	.023	-.003	.082
TO v TF	.014	.023	.027	.082
C v TF	.025	.023	.024	.082
Open-mindedness				
Across Conditions	.141.	.075	.152	.118
Training and Feedback	.181*	.080	.185	.139
Training Only	.133	.080	.164	.139
Control	.109	.080	.106	.139
C v TO	.024	.048	.058	.124
TO v TF	.047	.048	.020	.124
C v TF	.072	.048	.078	.124
Conscientiousness				
Across Conditions	-.008	.039	.523**	.145
Training and Feedback	.004	.047	.531**	.167
Training Only	-.003	.051	.541**	.167
Control	-.024	.047	.497**	.167
C v TO	.021	.045	.045	.142
TO v TF	.006	.045	-.010	.143
C v TF	.028	.045	.035	.143
Extraversion				
Across Conditions	-.184	.086	1.078***	.238
Training and Feedback	-.157	.088	1.163***	.266
Training Only	-.205*	.088	1.002**	.266
Control	-.192*	.087	1.069***	.266
C v TO	-.013	.032	-.068	.205
TO v TF	.048	.032	.016	.205
C v TF	.035	.032	.094	.205
Agreeableness				
Across Conditions	.208	.161	.118	.259
Training and Feedback	.203	.162	.104	.262
Training Only	.205	.162	.089	.262
Control	.218	.162	.160	.262
C v TO	-.014	.041	-.071	.065

TO v TF	-.002	.041	.015	.065
C v TF	-.016	.041	-.057	.065
Negative emotionality				
Across Conditions	.051	.065	.640***	.136
Training and Feedback	.058	.068	.622***	.178
Training Only	.066	.068	.626***	.178
Control	.025	.069	.675***	.178
C v TO	.041	.040	-.049	.202
TO v TF	-.007	.039	-.004	.203
C v TF	.033	.040	-.052	.202

Note. C = control condition, TO = training only condition, tf = training and feedback condition.
*** $p < .001$, ** $p < .01$, * $p < .05$

Figure 5

Accuracy Across Conditions for All Traits

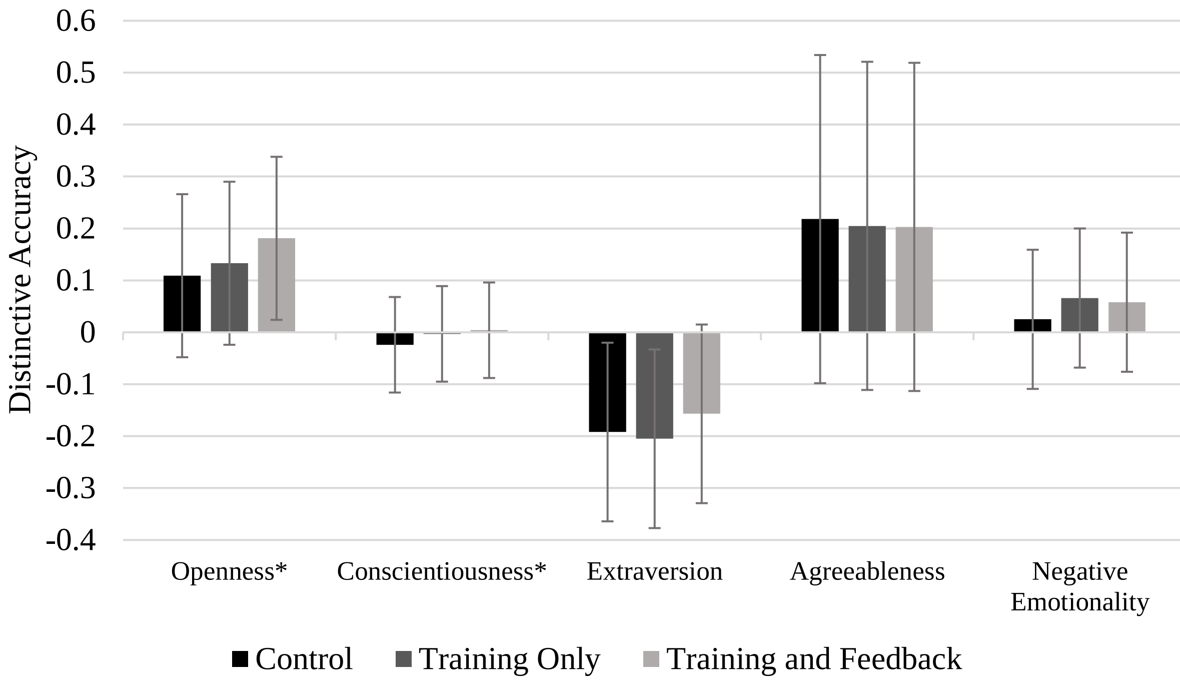


Note. Error bars depict 95% confidence intervals.

Using the condition as a moderator to examine accuracy of judging individual traits revealed no significant interactions, indicating the judgment accuracy of individual traits was not significantly influenced by training. Accuracy levels between conditions by trait are depicted in Figures 6 and 7. No consistent pattern emerged.

Figure 6

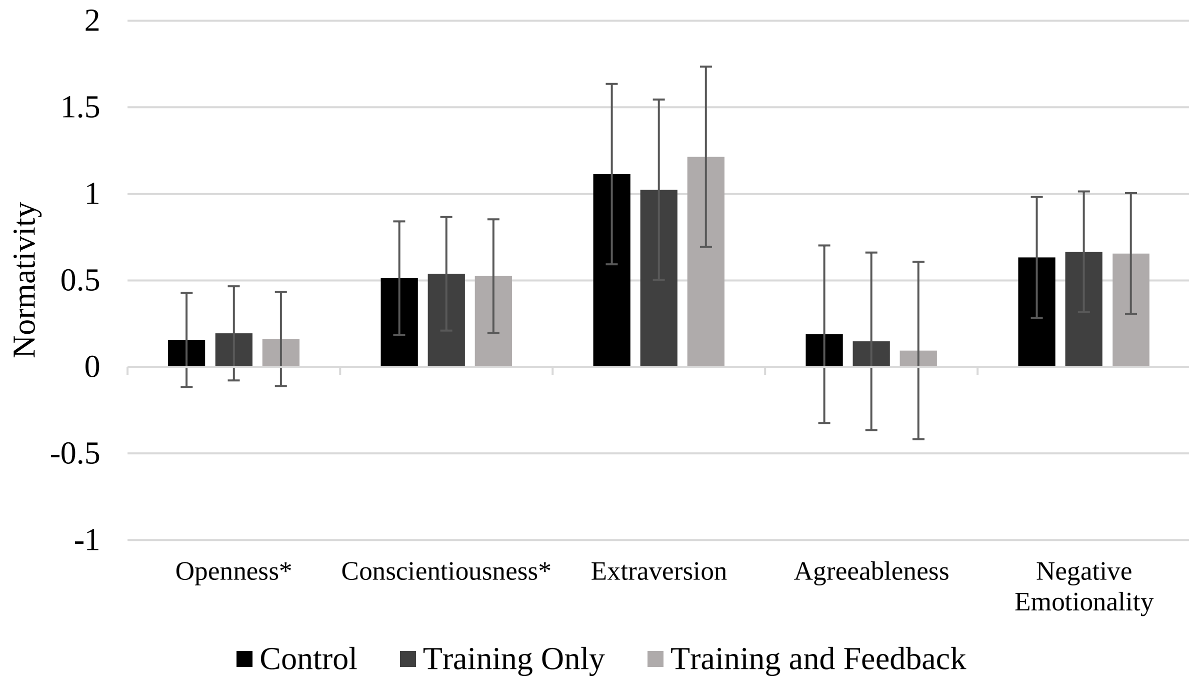
Distinctive Accuracy for Each Trait Between Conditions



Note. Error bars depict 95% confidence intervals.
* These traits were the focus of training.

Figure 7

Normativity for Each Trait Between Conditions



Note. Error bars depict 95% confidence intervals.
* These traits were the focus of training.

Chapter 9: Study 2 Discussion

The present study investigated the influence of two methods of personality judgement accuracy training on the accuracy of judgements made based on Twitter profiles. Both training methods were completely automated and administered online. One method consisted of only training, and the other consisted of training and personalized feedback. Additionally, the relationships between personality traits, social media use, and confidence in accurate judgments were explored. Overall, the findings provide insights into these research questions, although the results were largely unexpected.

Contrary to the initial hypothesis, the experimental groups that received training did not demonstrate significantly higher levels of accuracy compared to the control group. This suggests that this method of training, in the form of a video lecture on personality traits and valid but unutilized cues, is not an effective method to improve accuracy of judgements. The exact issue, or combination of issues, with this method of training is unclear. It is possible that a video lecture is not an interesting or engaging enough form of training. The manipulation checks ensured that any participants who completed the study did fully understand the main points of the training, even if they paid minimal attention to the video. It is possible that the cues that were selected for training were too narrow and specific to increase overall accuracy levels, or even trait-specific levels, and broader groupings of cues should have been the focus of training. It is also possible that asking participants to consider both conscientiousness and open-mindedness simultaneously was too confusing or cognitively taxing, and that more pronounced results would be evident if the focus was on only one trait. It is possible that bringing attention to the specific valid and unutilized cues through training did not increase accuracy because while these cues were unutilized by the previous set of judges, it may be that utilization patterns differed for the control group collected in this study. Essentially, it is possible that judges across conditions were utilizing cues in roughly the same ways, regardless of training. And finally, it is possible that the methodology for Study 1, which led to the design of the training, was flawed and that other valid cues were not considered or coded for.

Also contrary to the hypothesis, additional feedback about trait-level accuracy and specific cues did not significantly increase the level of judgement accuracy compared to training alone. This finding is surprising considering the past research on the role of feedback in improving judgment accuracy (e.g., Blanch-Hartigan & Cummings, 2021, Blanch-Hartigan et al., 2012). What's more, even the specific traits that were the focus of training were not judged with significantly higher levels of accuracy in the training conditions compared to control. Although distinctive accuracy for the trait of open-mindedness was found to follow the expected pattern, with the lowest level of accuracy for the control group, followed by the training only group, and the highest level of accuracy found in the training and feedback group, distinctive accuracy for conscientiousness and normativity for both traits followed a different pattern. In these cases, the control group exhibited the lowest levels of accuracy, followed by the training and feedback group, with the training only group exhibiting the highest levels of accuracy, although all differences between conditions were nonsignificant. This pattern could suggest that something about the specific method used of providing feedback was detrimental to accuracy. It is possible that the additional tasks required of participants in the training and feedback group increased cognitive load such that their ability to effectively detect and utilize cues was diminished. Past research has found that judges in situations with higher attentional loads are generally less accurate judges of personality (e.g., Biesanz et al., 2001; Candy & Kehoe, 1984). It is possible that showing participants their judgment rating alongside the actual rating, and asking them to compare the values, essentially evaluating how correct/incorrect they were, could promote feelings of test anxiety, and harm performance. Additionally, the extra time and effort required by participants to complete the feedback condition could have caused participants to rush through the ratings later in the study in an effort to complete the study within the 1-hour estimated time requirement. In future experiments, the same adjustment that was used for ensuring appropriate hourly pay between the control and other groups should be utilized between experimental groups as well.

When examining individual traits, it was found that conscientiousness, extraversion, and negative emotionality were judged with significant normativity across conditions, while open-mindedness and agreeableness were not judged with significant levels of normativity. This means that judges were able to accurately judge the targets as being similar to the average person for the traits of extraversion, conscientiousness, and negative emotionality, but not open-mindedness or agreeableness.

Judges were also unable to accurately perceive the distinctive aspects of targets' agreeableness and open-mindedness, or the other Big Five traits. Distinctive accuracy for extraversion was notably low across conditions, even achieving statistical significance in the negative direction in the control condition. This pattern of inaccurate judgements of extraversion on Twitter was also found in my thesis (Pedersen, 2020). It is interesting to note that extraversion, typically judged with high levels of accuracy, seems to be specifically difficult to judge based on Twitter profiles, or at least the Twitter profiles used in this study. Although Twitter is a social platform, the majority of social interaction between users happens in replies (i.e., comments), which were not captured in the screenshots as do not appear on the main page of one's Twitter profile. It seems likely that capturing these social interactions may lead to more accurate judgements of extraversion.

This study also explored the confidence individuals feel in their judgements, in general and in the context of a few social scenarios. While these feelings of confidence did not differ between experimental conditions, there were interesting correlations between judge personality and confidence. Participants who expressed higher confidence in their judgments generally exhibited lower levels of extraversion and conscientiousness, as well as higher levels of negative emotionality. This is interesting in light of past research that found more conscientious and less neurotic judges tend to actually be more accurate (Hall et al., 2016). The role of judge personality as a moderator of accuracy is beyond the scope of this study but is a potential avenue for future exploratory analyses. Interestingly, confidence in judgments about hiring was associated with both higher negative emotionality and lower social media use. Lower social media use was also associated with more confidence in judgements in relation to dating. It is possible that more limited exposure to social media means being exposed to a smaller volume of diverse opinions, perspectives, and content online, leading to a perception of general online consistency or agreement. This could lead to a greater sense of certainty about judgements, as they may be less sensitive to nuance in an online profile. Additionally, although conscientiousness was negatively related to general confidence in judgments, the trait was positively related to confidence in using judgements based on Twitter profiles to make good decisions about whether to befriend or date someone. This could reflect a difference in how more conscientious people handle judgements surrounding social decisions compared to more abstract evaluations of correctness vs incorrectness in judgements, with more conscientious people confidently making decisions about potential friends and dates, but less confident in their overall accuracy of judging traits.

Limitations

It is worth noting some limitations of the present study. First, the stimuli consisted of Twitter profiles collected in 2019-2020. The online environment, especially Twitter, has changed drastically since then, and it is possible that these judges would be more accurate if dealing with more contemporary stimuli. Second, the sample consisted of judges with lower levels of extraversion and higher open-mindedness compared to a representative US sample, which is a limit to generalizability. Research on judge personality has found mixed results in relation to extraversion (e.g., Kolar, 1995; Vernon, 1933) and open-mindedness (e.g., Christiansen et al., 2005; Lippa & Dietz; 2000), so it is unclear how judge personality differences may have influenced accuracy, but these differences between this sample and larger, more representative samples should be noted. Of course, the study also relied on self-reported measures which can be subject to biases and inaccuracies (Robins & John, 1997). And finally, it is always possible that utilizing research services such as CloudResearch Connect could result in lower quality data and results that fail to generalize. Although past research has found monetary incentives to have no significant impact on improving accuracy, given the context of CloudResearch Connect, it is possible that offering a "bonus" payment to the most accurate participants would increase the level of effort and attention paid by participants when recruited through this specific methodology.

The unique online environment and methodology provided by utilization of CloudResearch Connect also poses potential concerns for external generalizability, although there is also the distinct advantage of having a more diverse sample than the typical college student sample in terms of age, race/ethnicity, and location within the United States. It should be noted that while these results would likely replicate well in similar judge samples, the effect of judge-target similarity for gender and ethnicity has been found to influence accuracy (Letzring, 2010) and these targets were not necessarily demographically similar to judges. While 60% of judges were White, 83.3% of targets used were White. Additionally, judge gender broke down to 51.33% male/48.67% female, compared to targets which were 41.67% male/58.33% female. Age differences between targets and judges have been very minimally studied, and has been mostly concerned with judgements made by young adults of target of different ages (e.g., Krzyzaniak, 2020). The current sample, however, featured notably young targets aged 18-21 with a mean age of 19.58, and older judges, aged 18-73 with a mean age of 34.13. It is possible that having judges that are predominantly older than the targets could have negatively influenced accuracy by exacerbating differences between the judges and targets. Disregarding training, differences between judges and targets in understanding cues relevant to personality may be especially salient on SNSs, where memes and language-use are often unique. It is likely that if judges were more similar to targets, as was the case in my thesis study, that accuracy levels across conditions would have been higher overall, and more similar to levels observed in my thesis. However, while unlikely that a global increase in accuracy would result in any significant differences between training conditions, it is possible that college-aged individuals (who have recently experienced the proliferation of online education) may find a video-lecture and quiz training format more familiar and accessible than other age groups. Although some research conducted prior to 2020 suggests older students actually adapt better to online education (e.g., Xu & Jaggers, 2013), this research typically defines "older students" as any student above ages 23-25, which is not the age range captured by the judge sample in the present study. The extent to which demographic variables may influence the effectiveness of training methods should be more carefully considered and assessed in future research on improving judgement accuracy.

Conclusion

In conclusion, this study contributes to the understanding of what makes for effective and ineffective training for personality judgement accuracy, and also relationships between personality traits, social media use, and confidence in accurate judgments. Although the training and feedback provided in the experimental condition did not lead to significantly higher accuracy levels, these findings provide valuable insights for other researchers attempting to study personality judgement accuracy training, specifically on social media.

Chapter 10: General Discussion and Conclusion

The main goals of this study were to analyze the content of Twitter and Instagram profiles to gain a better understanding of the information used in making accurate judgments, to identify cues that could be used to train judges to improve their accuracy in making perceptions, and to assess the efficacy of two methods of training built on these cues. Additionally, a goal of Study 1 was to assess the hypothesis that higher anonymity on Twitter leads to lower judgment accuracy.

Study 1

After an extensive coding process, both principal component analysis and basic correlational analysis were used within a lens model framework to identify valid and utilized components and individual cues on Twitter and Instagram. Twitter profiles provided more valid and utilized cues compared to Instagram profiles, but considering the total cues coded for each platform, the proportions of valid and utilized cues were similar. However, while there were multiple significant valid and utilized cues on Instagram, there were none on Twitter, which helps to explain the difference in judgment accuracy levels between the profile types. This exploratory research cast a very wide net in the identification and coding of cues on Instagram and Twitter profiles, and can be used to inform future research. The specific findings of the exploratory lens model analyses, identifying valid and utilized cues in this study, could be used in accompaniment with past research of cues on social media to develop future code books and hypothesized cue groupings for lens model analyses.

There was no significant difference in anonymity between Instagram and Twitter, however a significant interaction between anonymity and normativity suggests that judges perceived targets who presented more anonymously on Twitter as less similar to the average person, leading to less normatively accurate judgments. Put another way, Twitter targets who were less anonymous were judged with higher levels of normativity. This could also suggest that less anonymous targets were seen more positively, as the normative profile highly correlates with a socially desirable profile (Biesanz, 2010). Considering this relationship to positivity, it may be that more anonymous targets are behaving in ways that are less socially desirable, and perhaps even experiencing some level of the online disinhibition effect (Suler, 2004), behaving in ways that would be inappropriate in person. Alternatively, judges may connect higher levels of anonymity to the potential for misleading or inauthentic information online, which is perceived as indicative of target untrustworthiness (DeAndrea & Walther, 2011). Although anonymity did not serve the predicted role in providing an explanatory mechanism for differences in accuracy between Instagram and Twitter, it seems that anonymity does play a role in personality judgement accuracy online, at least on Twitter.

Study 2

The results of Study 1 were used to identify which SNS platform and traits were the best candidates for training by selecting traits that had valid, unutilized cues and comparatively low levels of accuracy based on my thesis research. Twitter was chosen as the platform, and conscientiousness and open-mindedness as the traits to focus on in training. Study 2 found that training judges on these cues did not significantly increase personality judgment accuracy, even when feedback was provided. Unique patterns of accuracy for individual personality traits were uncovered between conditions, although no condition significantly differed from any other condition. It is promising however that, across traits, judges in both training conditions achieved significant levels of distinctive accuracy and normativity, while judges in the control condition only achieved significant levels of normativity. This pattern suggests that training may have exerted some influence, though these effects are either too minimal or inconsistent to reach significance thresholds.

Training also did not increase feelings of confidence about the accuracy of judgements generally or in regard to specific applications of hiring, friendship, or dating, although confidence did correlate with specific aspects of judge personality and SNS use. General confidence in the accuracy of one's judgments was related to lower extraversion and conscientiousness, and higher negative emotionality. Considering that past research has found more conscientious and less neurotic judges actually tend to be more accurate (Hall et al., 2016), the question rises of whether this confidence in unfounded. It is conceivable that prior research on the personality of the good judge may not replicate as well in the unique environment provided by social media, and Twitter specifically. The moderating influences of both judge personality and confidence in ratings, while beyond the scope of this dissertation, will certainly provide for interesting exploratory research. Confidence in one's judgements in relation to who to hire based on profiles was also related to higher negative emotionality as well as lower SNS usage. Lower SNS usage was also related to confidence about one's judgements in relation to who to go on a date with based on profiles. This relationship between lower SNS usage and confidence is an interesting one, as it may seem counterintuitive. In fact, past research found higher SNS usage to be predictive of more accurate judgements for both normativity and distinctive accuracy (Pedersen, 2020). This again could suggest that this confidence is unfounded. It is possible that more limited exposure to social media gives judges a false impression of consistency online, essentially developing and relying on a stereotype of individuals who are active on social media, or on Twitter specifically, and this could lead to overconfidence. Additionally, while lower conscientiousness was correlated with overall confidence in judgments, the opposite was true for confidence in using judgments to make sound decisions regarding befriending or dating individuals, with more conscientious judges exhibiting greater confidence in these decisions. This observation may indicate a distinction in how individuals with higher levels of conscientiousness approach social decision-making compared to their evaluation of abstract judgments of correctness or incorrectness. Specifically, individuals with greater conscientiousness may display confidence in making decisions about potential friends and dates, while being less certain about the overall accuracy of their trait assessments.

The specific hypothesis that was tested in Study 2 was largely unsupported, in that neither simple training nor training with personalized feedback about performance significantly improved judgement accuracy. Comparing the specific method of training used in this study to past research that has successfully improved judgement accuracy, a few key differences could potentially help to explain the inefficacy of training in this study. First and foremost, this training was entirely administered online and to individual participants, compared to past research which has used in-lab designs and small groups of participants (e.g., Powell & Goffin, 2009; Powell & Goffin, 2016). Considering the potentially cognitively difficult task of learning about and retaining cues relating to two different traits, and the somewhat tedious tasks required of participants, it is possible that providing a distraction-free environment, the guidance of a research assistant, and the social pressure of completing the study in a small group may be essential for effective training. Additionally, some successful past studies had participants provide their first judgement ratings prior to receiving training (Powell & Goffin, 2009; Powell & Goffin, 2016), as opposed to the present study which had all judgement ratings occur after training. It is possible that allowing participants to provide judgements prior to any training allows them to reflect on their recent judgement process while receiving training, perhaps making training seem more interesting and applicable. Participants in these same past studies also discussed their judgements and use of cues in small groups as part of training, encouraging even further reflection and understanding of the judgement process. An attempt to replicate this process was utilized in the current study, as participants were asked to write out which cues they used in the training and feedback condition, but this clearly lacks the social aspect present in the original studies. Finally, these past studies also provided an additional incentive in that the top 10% most accurate raters received prizes of $20. As mentioned in Study 2's discussion section, this sort of additional incentive may have proved especially effective in the present study as the primary reason behind participating in studies using CloudResearch Connect is to make money.

In regards to understanding the results of Study 2, it may be helpful to reexamine some of the basic attributes of the targets and their online behavior, as analyzed in Study 1. The personality of the targets used in this study did not differ meaningfully from normative samples, so it is unlikely that the characteristics of the targets themselves contribute to these unusually low levels of accuracy and resistance to improvement through training. However, the behavior exhibited by targets on Twitter profiles, and how this behavior related to personality, is counterintuitive. For example, the valid cues for agreeableness, a trait characterized by friendliness, included less positive facial expressions, less smiling, and more sexually explicit words. The valid cues for negative emotionality included more themes of optimism, gratitude, and achievement. Many valid cues across traits were utilized by judges in Study 1 in the opposite direction, exemplifying how counterintuitive these relationships between traits and behavior were.

This study utilized the Realistic Accuracy Model framework to focus on the stages of detection and utilization, which are under the control of the judge. Training focused on these stages and encouraged judges to detect specific cues and taught them how to utilize their observations to make judgments of the specific traits of open-mindedness and conscientiousness. However, within this study, it seems likely that the very first step of RAM, relevance, was not completed by the targets. The cues displayed by targets on Twitter seem to have lacked relevance to their underlying personality traits, at least compared to how personality is consistently displayed across other situations and contexts. It is possible that the environment of Twitter is unique in that it is a “strong” situation, meaning that targets act similarly to one another regardless of actual personality (Ickes et al., 1997). In this way, cues that are being made available by targets are less relevant to underlying personality traits. Considering this in relation to the concept of the Density Distributions approach to personality traits (Fleeson, 2001) wherein traits are conceptualized as distributions of behaviors and states, it is possible that states targets are in while on Twitter and/or the behavior displayed on Twitter exists in the tails of targets’ hypothetical bell curves. If this were the case, then Twitter profiles would not accurately reflect a target’s self-report of their general personality traits. Perhaps an interesting avenue for future research, personality states measured over time while using Twitter or other online platforms may differ from offline personality states. Similarly, direct comparisons between in-person behavior and interactions and online behavior interactions could help to shed light on the strength of situations in online environments.

Judges were able to achieve significant normativity for some traits across experimental conditions: conscientiousness, extraversion, and negative emotionality. This could indicate that judges were relying more on what they think the average person is like when making these judgements. One might expect, if this was the case, that judges in the experimental conditions that received specific information about how these targets exhibit the trait of conscientiousness would have lower levels of normativity, but results did not indicate this. Additionally, the reasoning behind why judges would then not rely as heavily on what they think the average person is like in regards to agreeableness and open-mindedness is unclear. However, although nonsignificant in this study, both here and in my thesis, agreeableness had the highest levels of distinctive accuracy, suggesting that perhaps something about Twitter profiles leads judges to focus more on distinctive information pertaining to agreeableness and rely less on normative information. And, although not significantly different across conditions, open-mindedness in the training and feedback condition was the only trait for which judgements reached significant distinctive accuracy, while open-mindedness in the other conditions had the second-highest accuracy levels behind agreeableness, which could also indicate a shifting away from reliance on normative information in favor of more unique information about each target.

Judges failed to consistently achieve significant distinctive accuracy for any other trait. In fact, for the trait of extraversion, judges achieved significant levels of inaccuracy, meaning that less extraverted people were perceived with high levels of extraversion while more extraverted people were judged as having lower levels. This could again be indicative of unique behavior of targets on Twitter, and even a version of the online disinhibition effect, wherein targets behave differently online than they normally would. It is possible that Twitter specifically, with its length constraints, is more accessible and enjoyable for introverts, as less extraverted people tend to write more briefly and concretely (Gill & Oberlander, 2002). More extraverted people, on the other hand, may find these length constraints more restricting of expression, and so this particular aspect of their personality may not be expressed. It is also possible that more introverted people, with the reduced social pressure provided by the asynchronous nature of CMC, may find it easier to share thoughts and opinions in more expressive ways on Twitter than in other contexts. These factors could potentially combine to result in profiles wherein the more extraverted people appear introverted, and vice-versa. Overall, the significantly inaccurate judgements made for extraversion are interesting for their novelty and should be explored further.

It is unclear what specific aspect of the training methodologies tested resulted in inefficacy. While it is possible that there is issue with the delivery of the training, as explained in Study 2's discussion and above, it is also possible that the cues that were the focus of training where just too counterintuitive for judges to overcome in order to achieve accuracy. If the valid unutilized cues that were discovered in Study 1 had been able to be more clearly explained and related back to the traits of interest, perhaps training would have been more effective. For example, judges were trained about the definition of conscientiousness (e.g., organized, responsible, reliable, etc.) and a cue that someone on Twitter may be high in conscientiousness is the use of more swear words, however no explanation as to how or why swear words would be indicative of conscientiousness was provided. If cues uncovered in Study 1 had been the sort that could clearly relate to the definitions of traits (e.g., for conscientiousness perhaps more content pertaining to school, less spelling errors, etc.), training may have been more intuitive and more effective.

Future Directions

This study presents multiple avenues for potential areas of interest and future study. First, focusing on Study 1, the measurement of anonymity on Twitter profiles could be reexamined and expanded. Anonymity in this study was measured by a combination of objective and subjective ratings of various pieces of information that could have been used to find or identify someone in an offline context based on their profile. This is just one way to conceptualize anonymity, however. Another way, and perhaps more at the forefront of people's minds as it is more relevant within the context of job hunting, is what level of information someone would need in order to find a given online profile. Additionally, even if a profile is clearly not anonymous, exploring the extent to which a Twitter user is followed by their offline social circle or thinks that their behavior is being perceived by that social circle might relate more directly to behavior online.

Secondly, while this study covered a wide range of cues on Twitter, there are likely more valid and utilized cues that were not captured by coding, specifically on other pages beyond the main profile page, such as the "Replies" and "Likes" tabs. In order to better inform future coding, researchers should consider pilot studies wherein participants are asked to explore a target's live/dynamic Twitter profile to form a judgement in order to assess which pages are most important in the process in real-world scenarios. Additionally, use of eye-tracking or user-experience-style methodology to help identify areas for future coding would likely help in identifying which cues are most likely to be utilized by judges. Also, based on the experience of coding Twitter profiles at roughly the same time as the mainstream popularization of AI tools like ChatGPT, it seems likely that this technology could easily be utilized in the process of coding content of social media profiles. The potential for AI to assist in coding would increase both the efficiency and potentially the accuracy of codes, reducing variability surrounding human interpretation and human error, making research like this less labor intensive in the future.

Additionally, research looking into the seemingly unique behavior of targets on Twitter, specifically in direct comparison to other online behaviors of the same targets, would help to shed light on this study's results. Using a within-subjects approach to comparing valid cues on multiple online platforms could help explain the ways in which Twitter is a potentially unique online social environment. Also, as discussed previously, comparing the frequency and variability of personality states and behaviors on Twitter to states and behaviors offline could potentially explain the ways in which online environments interact with personality expression.

This research tested two methods of online personality judgment accuracy training, neither of which were successful, although the exact reason(s) for this are unclear. Although past research that exhibited successful training was in-person, finding ways to create trainings that are asynchronous and provided remotely will have implications of the potential widespread utility of such trainings. For example, an easily distributed training course on improving personality judgement accuracy based on online profiles could be immensely useful for HR professionals and others involved in hiring decisions. Future research should continue to test different training methodologies online, perhaps by narrowing the scope and systematically testing different pieces of adapting training and feedback to asynchronous online administration. For example, the focus of training could be narrowed to only one trait, or even facets of traits to reduce the cognitive effort required of the judge. Future research should test specific pieces of the training process as well, such as whether having judges provide an initial target rating prior to training actually increases efficacy, or whether the social component of past successful training can be replaced with automated processes such as chat-bots.

Regarding the accuracy of personality judgements made online a bit more broadly, other important research questions exist about the role of social media profiles in conjunction with in-person information. Individuals may increasingly be “meeting” online prior to meeting in-person, while it used to be much more common to meet in-person and look up someone’s social media profile after an initial meeting. Social media profiles can be both used to form an initial judgement that may be adjusted upon meeting in-person and also to adjust a prior in-person judgement. The extent to which these two sources of information can be combined to achieve the most accurate personality judgements, and whether the order of the information received is important or not, has not been thoroughly explored yet has important implications for modern social interactions and relationships.

Conclusion

In conclusion, as the use of social networking sites continues to grow and more aspects of daily life transition to online spaces, understanding how people perceive and judge each other in these contexts becomes increasingly important. While both Instagram and Twitter were found to contain various valid and utilized cues for forming accurate personality judgments, Twitter profiles provided for significantly lower levels of accuracy, likely due in part to the lack of valid cues being utilized. Anonymity, though not explaining the differences in accuracy between Instagram and Twitter, does play a role in how normatively targets are perceived, with less anonymous targets being perceived with higher normative accuracy.

This study contributes to the literature on training and improving personality judgement accuracy, and is, to my knowledge, the first study that focused training on social media profiles. Although training was ineffective, it still provides valuable insights for researchers and useful information to help inform methodological decisions in future studies.

By understanding the cues used in online contexts, we can gain insights into how people form impressions and make judgments on social media. This knowledge has implications for how individuals present themselves online and how others perceive and interpret their digital identities. Furthermore, the study's findings contribute to our understanding of the complexities of personality judgments in the digital age and highlight the need for further research in this area.

As online interactions become increasingly prevalent, it is crucial to explore the nuances of social media behavior and its impact on perception. Future studies can delve deeper into the specific cues that contribute to accuracy or inaccuracy in personality judgments on different platforms. This study sheds light on the complexities of personality judgments in online contexts and provides valuable insights into the cues used for forming accurate perceptions on Twitter and Instagram. Understanding these dynamics is essential as we navigate the evolving landscape of digital communication and strive for more accurate and nuanced interpersonal judgments in the realm of social media.

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Appendix A

Codebooks

Codebook – Twitter

1. Once you have identified the profile you are coding using the Tracking Sheet, open up the associated image and Excel spreadsheet in the Box folders, identified by the Participant ID # (e.g., 54.jpeg and 54.csv)
2. Follow the order present in the Excel spreadsheet, also repeated below with more context/information.
3. Throughout coding, make note of any issues/questions/comments you have in the Tracking Sheet.
4. Begin with the Top of the Profile/Basics. This is mostly objective and straight-forward, except for two subjective ratings - overall anonymity of Profile Bio and personnel-ness of the Profile Bio.
5. The next step is the section titled Tweet Counts. Again, this is objective and straight-forward. All codes are numeric. It is not necessary to read the tweets at this step.
6. Written Content. This section is done in three passes or steps. In Step 1, carefully read each Tweet, scanning and counting each specific instance of swear words, sexually explicit words, emojis/emoticons, initialisms, exaggerated spellings, and misspellings. In Step 2, again read each Tweet, this time looking for the listed content types. Note that specific instances of other people are numeric, while the general content is on a 1-5 scale. After reading each Tweet twice, you should be able to perform Step 3 without rereading the entire profile, rating the profile owner's emotions and attitudes. This will be subjective.

7. Images. This is again an objective and numeric code.
8. Owner appearance. Based on your read of the profile and the images you think are of the profile owner, rate their appearance. This will be subjective. At the end of the 1-5 scale ratings, indicate how old you estimate the person to be using one number.
9. Double-check you have completed the entire Excel spreadsheet and upload to Box.

All Twitter emojis can be copied from the following website: https://emojipedia.org/twitter/ - paste into cell using "Match Destination Formatting (M)" to insert a standardized description of the emoji.

Cue	Responses
TOP OF PROFILE/BASICS	
Profile picture of owner?	Yes/No
If no, what is the profile picture of?	Free response – briefly describe
Anonymity of profile owner	1 clearly of face, owner only 2 face unclear (far away/ filtered/ distorted/partially hidden), owner only 3 clearly of face, but with others 4 unclear face, and with others 5 avatar, drawing, or other artistic representation of owner 6 image not of owner
Tweets	#

Followers	#
Following	#
Likes	#
Banner photo?	Yes/No
Banner photo content (can be multiple)	1 People 2 Animals 3 Nature/Outdoors 4 Art 5 Quote 6 Other
Is the user's name underneath the profile picture and above their Twitter username?	1 first and last 2 just first 3 other 4 no name
If other, what is written in this place?	Free response – include full text
Does the USERNAME…	1 include full first AND last name 2 include full first OR last name 3 include portions of first and/or last name 4 seemingly include nickname/misspellings of name(s) 5 seemingly no inclusion of name

Does the USERNAME…	1 contain identifying information such as location, title, birthyear, etc. 2 contain no identifying information
Is there a bio?	Yes/No
Bio word count	#
Bio emoji count (including name)	#
Anonymity in Bio	1-5 with 1) a lot of identifying information (such as specific location, age, school, job, names/links to family/significant others) and 5) no identifying information
Personal-ness of Bio	1-5 with 1 being most personal and 5 being least personal
Location specificity	1 – Town 2 – State 3 – Region (e.g., PNW) 4 – Country (including flag emojis) 5 – No location information
Links/info about other SNS in Bio	#
Joined Date	Free response
Birthday	Yes/No
Number of photos/videos in sidebar count	#
Pinned tweet	Yes/No

Pinned tweet content	Free response – include full text
TWEET COUNTS	
Original tweets in screenshot	#
Likes on original tweets (total)	#
Replies to original tweets (total)	#
Retweets on original tweets (total)	#
Retweets in screenshot	#
NUMBER OF TIMES RETWEETED TWEETS HAVE BEEN RETWEETED	
Under 10	#
10-100	#
100-1k	#
1k-10k	#
10k-100k	#
100k+	#
WRITTEN CONTENT	
Round 1: Counting Specific Features	
Swear words	#
Sexually explicit words	#
Emojis/emoticons	#
Initialisms	#
Exaggerated spellings (seemingly purposeful)	#
Misspellings (seemingly accidental)	#

Round 2: Content Types	
Social Processes	
- Pertaining to non-romantic relationships	1(not at all) – 5(very much)
- Pertaining to romantic relationships	1(not at all) – 5(very much)
- Mentions of Family	#
- Mentions of Friends	#
- Mentions of Partners	#
- Mentions of Others	#
Pertaining to Academics	1(not at all) – 5(very much)
Pertaining to Work	1(not at all) – 5(very much)
Pertaining to Movies/TV	1(not at all) – 5(very much)
Pertaining to Music	1(not at all) – 5(very much)
Pertaining to Art	1(not at all) – 5(very much)
Pertaining to Sports	1(not at all) – 5(very much)
Pertaining to Other Hobbies/Interests	1(not at all) – 5(very much)
Sexual content	1(not at all) – 5(very much)
Political content	1(not at all) – 5(very much)
Religious content	1(not at all) – 5(very much)
Round 3: Emotions/Attitudes	
Positive Emotion	
- General positivity	1(not at all) – 5(very much)
- Optimism	1(not at all) – 5(very much)
- Achievement	1(not at all) – 5(very much)

- Gratitude	1(not at all) – 5(very much)
Negative Emotion	
- General negativity	1(not at all) – 5(very much)
- Stress/Anxiety	1(not at all) – 5(very much)
- Sadness	1(not at all) – 5(very much)
- Anger	1(not at all) – 5(very much)
Humor	
- General amount of humor	1(not at all) – 5(very much)
- Memes	1(not at all) – 5(very much)
- Sarcasm	1(not at all) – 5(very much)
IMAGES	
Number of images (in feed i.e., not including sidebar count)	#
Self-images/selfies	#
Images of self with others	#
Images of only others	#
Number of diverse others across posts	#
Number of images without people	#
Number of videos	#
OWNER APPEARANCE (if applicable)	Utilize all photos.
Smiling	1(not at all) – 5(very much)
Positive facial expression	1(not at all) – 5(very much)
Neutral facial expression	1(not at all) – 5(very much)

Negative facial expression	1(not at all) – 5(very much)
Dominant facial expression/pose	1(not at all) – 5(very much)
Stylish (clothes, hair, makeup)	1(not at all) – 5(very much)
Attractive	1(not at all) – 5(very much)
Neat	1(not at all) – 5(very much)
Posed	1(not at all) – 5(very much)
Candid	1(not at all) – 5(very much)
How old do you think this person is?	#

Codebook – Instagram

1. Once you have identified the profile you are coding using the Tracking Sheet, open up the associated image and Excel spreadsheet in the Box folders, identified by the Participant ID # (e.g., 54.jpeg and 54.csv)
2. Follow the order present in the Excel spreadsheet, also repeated below with more context/information.
3. Throughout coding, make note of any issues/questions/comments you have in the Tracking Sheet.
4. Begin with the Top of the Profile/Basics. This is mostly objective and straight-forward, except for two subjective ratings - overall anonymity of Profile Bio and personnel-ness of the Profile Bio.
5. The next step is titled Scan Images. Simply scan the images for the icons that indicate multiple posts and video posts. Additionally, scan the images and bio for any swear words and total them here.
6. The next step is Image Content. This is objective and numeric and consists of counting people, animals, text, objects, and the outdoors in images. You may have to make some judgement calls if you cannot tell if an individual is the same person between photos – this can get tricky with pictures of families that look alike or large friend groups. Do your best and make a note in the tracking sheet.
7. Owner appearance. Based on all of the images you think are of the profile owner, rate their appearance. This will be subjective. At the end of the 1-5 scale ratings, indicate how old you estimate the person to be using one number.

8. Finally, look for themes within the images pertaining to the categories below. These ratings will be subjective.
9. Double-check you have completed the entire Excel spreadsheet and upload to Box.

Cue	Responses
TOP OF PROFILE/BASICS	
Profile picture of owner?	Yes/No
If no, what is the profile picture of?	Free response – briefly describe
Anonymity of profile owner picture	1 clearly of face, owner only 2 face unclear (far away/ filtered/ distorted/partially hidden), owner only 3 clearly of face, but with others 4 unclear face, and with others 5 avatar, drawing, or other artistic representation of owner 6 image not of owner
Posts	#
Followers	#
Following	#
Profile owners name in bold above bio?	1 first and last 2 just first 3 other 4 no name

If other, describe	Free response – include full text
Does the USERNAME…	1 include full first AND last name 2 include full first OR last name 3 include portions of first and/or last name 4 seemingly include nickname/misspellings of name(s) 5 seemingly no inclusion of name
Does the USERNAME…	1 contain identifying information such as location, title, birthyear, etc. 2 contain no identifying information
Is there a bio?	Yes/No
Bio word count	#
Bio emoji count (including name)	#
Anonymity in Bio	1-5 with 1) a lot of identifying information (such as specific location, age, school, job, names/links to family/significant others) and 5) no identifying information
Personal-ness of Bio	1-5 with 1 being most personal and 5 being least personal
Location specificity	1 – Town 2 – State 3 – Region (e.g., PNW)

	4 – Country (including flag emojis) 5 – No location information
Links/info about other SNS in Bio	#
Number of story highlights (circles beneath bio)	#
SCAN IMAGES	
Number of multiple posts (icon on image)	#
Number of video posts (icon on image)	#
Swear words in screenshot	#
IMAGE CONTENT	
Self-images/selfies	#
Images of self with others	#
Images of only others	#
Number of unique others across posts	#
Number of images without people	#
Number of images with animals	#
Number of images outdoors	#
Number of images with imbedded text	#
Number of photos of inanimate objects	#
OWNER APPEARANCE (if applicable) Utilize all photos.	
Smiling	1(not at all) – 5(very much)
Positive facial expression	1(not at all) – 5(very much)

Neutral facial expression	1(not at all) – 5(very much)
Negative facial expression	1(not at all) – 5(very much)
Dominant facial expression/pose	1(not at all) – 5(very much)
Stylish (clothes, hair, makeup)	1(not at all) – 5(very much)
Attractive	1(not at all) – 5(very much)
Neat	1(not at all) – 5(very much)
Posed	1(not at all) – 5(very much)
Candid	1(not at all) – 5(very much)
How old do you think this person is?	#
IMAGE THEMES	
Images pertaining to Movies/TV	1(not at all) – 5(very much)
Images pertaining to Music	1(not at all) – 5(very much)
Images pertaining to Art	1(not at all) – 5(very much)
Images pertaining to Sports/Fitness	1(not at all) – 5(very much)
Images pertaining to Other Hobbies/Interests	1(not at all) – 5(very much)
Images pertaining to Religion	1(not at all) – 5(very much)
Images pertaining to Politics	1(not at all) – 5(very much)

Appendix B

Table B1

Instagram Cue Correlation Table

Correlation

Pearson's Correlations

Variable		Profile Picture of Owner	Anonymity of profile owner	Posts	Followers	Following	Bio word count	Anonymity in Bio	Location specificity	Links/info about other SNS in Bio	Self-images/selfies	Images of self with others	Images of only others	Number of unique others across posts	Number of images without people	Number of images with animals	Number of images outdoors	Number of photos of inanimate objects	Smiling
1. Profile Picture of Owner	Pearson's r	—																	
	p-value	—																	
2. Anonymity of profile owner	Pearson's r	0.530***	—																
	p-value	< .001	—																
3. Posts	Pearson's r	-0.041	-0.164	—															
	p-value	0.773	0.252	—															
4. Followers	Pearson's r	-0.163	0.064	0.490***	—														
	p-value	0.252	0.656	< .001	—														
5. Following	Pearson's r	-0.142	0.244	-0.005	0.509***	—													
	p-value	0.320	0.085	0.971	< .001	—													
6. Bio word count	Pearson's r	-0.152	-0.333*	0.126	-0.042	-0.009	—												
	p-value	0.287	0.017	0.378	0.770	0.948	—												
7. Anonymity in Bio	Pearson's r	0.157	0.033	-0.053	-0.283*	-0.197	-0.452***	—											
	p-value	0.270	0.816	0.711	0.044	0.166	< .001	—											
8. Location specificity	Pearson's r	0.084	0.041	-0.024	-0.295*	0.081	-0.147	0.647***	—										
	p-value	0.558	0.778	0.869	0.036	0.572	0.304	< .001	—										
9. Links/info about other SNS in Bio	Pearson's r	-0.088	-0.040	0.101	0.177	0.122	0.255	-0.381**	-0.129	—									
	p-value	0.539	0.783	0.479	0.213	0.394	0.071	0.006	0.369	—									
10. Self-images/selfies	Pearson's r	-0.096	-0.299*	-0.068	0.069	-0.192	-0.011	-0.141	-0.245	-0.012	—								
	p-value	0.502	0.033	0.634	0.631	0.176	0.939	0.325	0.083	0.935	—								
11. Images of self with others	Pearson's r	-0.019	0.221	-0.148	0.299*	0.297*	-0.186	-0.059	-0.103	-0.111	-0.302*	—							
	p-value	0.896	0.118	0.299	0.033	0.034	0.191	0.682	0.471	0.438	0.031	—							
12. Images of only others	Pearson's r	0.102	0.437**	0.264	0.107	7.551×10^{-4}	-0.274	0.147	0.154	-0.075	-0.377**	-0.048	—						
	p-value	0.474	0.001	0.061	0.455	0.996	0.052	0.303	0.281	0.602	0.006	0.737	—						
13. Number of unique others across posts	Pearson's r	0.005	0.055	-0.024	0.172	0.016	-0.136	-0.084	-0.263	-0.097	0.046	0.086	-0.073	—					
	p-value	0.973	0.702	0.865	0.227	0.912	0.342	0.556	0.063	0.499	0.751	0.549	0.613	—					
14. Number of images without people	Pearson's r	0.019	-0.212	0.033	-0.414**	-0.136	0.365**	0.076	0.241	0.137	-0.371**	-0.640***	-0.132	-0.102	—				
	p-value	0.896	0.135	0.818	0.003	0.342	0.009	0.594	0.088	0.337	0.007	< .001	0.354	0.475	—				
15. Number of images with animals	Pearson's r	-0.090	-0.199	0.446**	0.100	0.059	0.120	0.056	0.015	-0.148	-0.082	-0.153	0.103	-0.139	0.136	—			
	p-value	0.530	0.161	0.001	0.486	0.680	0.401	0.696	0.914	0.299	0.568	0.283	0.473	0.332	0.342	—			
16. Number of images outdoors	Pearson's r	0.093	0.232	-0.075	0.222	0.108	-0.365**	0.098	-0.056	-0.279*	0.059	0.328*	-0.008	0.235	-0.408**	-0.123	—		
	p-value	0.517	0.102	0.602	0.117	0.451	0.008	0.492	0.698	0.047	0.683	0.019	0.955	0.097	0.003	0.390	—		

Variable		Profile Picture of Owner	Anonymity of profile owner	Posts	Followers	Following	Bio word count	Anonymity in Bio	Location specificity	Links/info about other SNS in Bio	Self-images/selfies	Images of self with others	Images of only others	Number of unique others across posts	Number of images without people	Number of images with animals	Number of images outdoors	Number of photos of inanimate objects	Smiling
17. Number of photos of inanimate objects	Pearson's r	0.086	-0.148	-0.045	-0.375**	-0.195	0.151	0.143	0.242	0.140	-0.303*	-0.402**	-0.083	-0.165	0.695***	-0.032	-0.468***	—	
	p-value	0.548	0.300	0.756	0.007	0.171	0.290	0.316	0.088	0.326	0.030	0.003	0.564	0.246	< .001	0.822	< .001	—	
18. Smiling	Pearson's r	0.150	0.300*	-0.114	0.150	0.070	-0.489***	0.238	-0.041	-0.330*	-0.157	0.722***	0.098	0.214	-0.613***	-0.077	0.427**	-0.407**	—
	p-value	0.295	0.032	0.427	0.292	0.624	< .001	0.093	0.773	0.018	0.270	< .001	0.496	0.132	< .001	0.591	0.002	0.003	—
19. Positive facial expression	Pearson's r	0.123	0.252	-0.160	0.123	0.021	-0.424**	0.241	-0.092	-0.337*	-0.129	0.702***	0.072	0.191	-0.601***	-0.086	0.376**	-0.285*	0.935***
	p-value	0.390	0.074	0.262	0.389	0.885	0.002	0.088	0.520	0.016	0.367	< .001	0.617	0.179	< .001	0.547	0.007	0.043	< .001
20. Neutral facial expression	Pearson's r	-0.118	-0.310*	0.017	-0.115	-0.004	0.389**	-0.288*	-0.088	0.420**	0.356*	-0.627***	-0.233	-0.145	0.413**	0.055	-0.396**	0.265	-0.863***
	p-value	0.411	0.027	0.906	0.423	0.978	0.005	0.041	0.539	0.002	0.010	< .001	0.100	0.311	0.003	0.701	0.004	0.060	< .001
21. Negative facial expression	Pearson's r	-0.068	-0.040	0.441**	0.080	-0.060	-0.029	-0.083	0.088	-0.010	0.263	-0.402**	0.152	-0.121	0.077	0.129	-0.204	0.166	-0.450***
	p-value	0.635	0.778	0.001	0.576	0.675	0.841	0.563	0.539	0.943	0.062	0.003	0.288	0.398	0.593	0.365	0.151	0.244	< .001
22. Dominant facial expression/pose	Pearson's r	-0.052	-0.038	0.030	0.181	-0.114	0.121	-0.553***	-0.448***	0.262	0.465***	-0.107	-0.140	-0.096	-0.225	-0.002	0.097	-0.101	-0.252
	p-value	0.719	0.790	0.836	0.204	0.425	0.397	< .001	< .001	0.064	< .001	0.456	0.328	0.502	0.112	0.989	0.500	0.479	0.074
23. Attractive	Pearson's r	-0.114	0.155	-0.017	0.532***	0.203	-0.260	-0.086	-0.207	-0.074	0.343*	0.477***	-0.023	0.185	-0.737***	-0.092	0.296*	-0.442**	0.465***
	p-value	0.425	0.276	0.904	< .001	0.153	0.066	0.549	0.144	0.606	0.014	< .001	0.870	0.195	< .001	0.519	0.035	0.001	< .001
24. Neat	Pearson's r	-0.110	0.232	-0.035	0.299*	0.018	-0.202	0.039	-0.198	-0.252	0.173	0.596***	-0.034	0.180	-0.698***	-0.053	0.429**	-0.601***	0.653***
	p-value	0.443	0.101	0.807	0.033	0.900	0.155	0.784	0.163	0.074	0.224	< .001	0.812	0.207	< .001	0.709	0.002	< .001	< .001
25. Posed	Pearson's r	-0.090	-0.021	-0.013	0.247	-0.014	-0.166	-0.160	-0.245	-0.249	0.380**	0.336*	0.007	0.070	-0.592***	0.125	0.165	-0.452***	0.546***
	p-value	0.528	0.883	0.926	0.080	0.925	0.246	0.262	0.083	0.078	0.006	0.016	0.959	0.626	< .001	0.380	0.248	< .001	< .001
26. Candid	Pearson's r	0.143	0.173	-0.096	-0.056	-0.048	-0.308*	0.030	-0.038	-0.107	0.104	0.080	-0.044	0.213	-0.195	-0.101	0.387**	-0.154	0.007
	p-value	0.318	0.224	0.504	0.695	0.737	0.028	0.833	0.791	0.453	0.469	0.578	0.761	0.134	0.170	0.480	0.005	0.279	0.959
27. Pertaining to Academics	Pearson's r	-0.108	-0.105	-0.141	0.011	0.128	0.199	-0.495***	-0.251	0.046	0.107	0.063	-0.234	0.086	0.019	-0.127	-0.137	-0.091	-0.114
	p-value	0.451	0.464	0.324	0.940	0.372	0.162	< .001	0.076	0.751	0.454	0.661	0.098	0.549	0.897	0.373	0.339	0.526	0.426
28. Pertaining to Work	Pearson's r	0.122	-0.044	0.253	-0.090	-0.069	-0.058	0.113	0.216	0.122	-0.099	-0.205	0.069	-0.034	0.227	0.094	-0.281*	0.366**	-0.128
	p-value	0.395	0.759	0.073	0.530	0.630	0.687	0.430	0.127	0.395	0.488	0.148	0.631	0.812	0.108	0.511	0.045	0.008	0.369
29. Pertaining to Movies/TV	Pearson's r	0.233	-0.006	0.262	-0.126	-0.213	0.101	0.048	0.192	0.058	-0.170	-0.375**	0.279*	-0.095	0.356*	0.126	-0.218	0.156	-0.310*
	p-value	0.101	0.964	0.063	0.380	0.134	0.482	0.736	0.178	0.684	0.232	0.007	0.047	0.508	0.010	0.378	0.124	0.275	0.027
30. Pertaining to Music	Pearson's r	0.059	-0.136	-0.073	-0.167	-0.136	0.034	0.140	0.107	0.249	-0.024	-0.248	-0.088	-0.160	0.267	0.052	-0.367**	0.546***	-0.192
	p-value	0.679	0.340	0.612	0.241	0.342	0.814	0.326	0.457	0.079	0.865	0.080	0.539	0.261	0.059	0.718	0.008	< .001	0.176
31. Pertaining to Art	Pearson's r	0.389**	0.070	-0.027	-0.289*	-0.166	0.086	0.162	0.210	-0.118	-0.118	-0.296*	-0.169	-0.017	0.455***	0.157	-0.144	0.513***	-0.246
	p-value	0.005	0.626	0.849	0.040	0.244	0.550	0.256	0.140	0.411	0.411	0.035	0.235	0.906	< .001	0.270	0.313	< .001	0.082
32. Pertaining to Sports/Fitness	Pearson's r	-0.073	0.102	-0.039	0.220	0.147	-0.064	-0.308*	-0.132	0.038	-0.150	0.471***	-0.038	0.153	-0.326*	-0.083	0.415**	-0.318*	0.292*
	p-value	0.609	0.478	0.784	0.121	0.303	0.657	0.028	0.355	0.792	0.294	< .001	0.791	0.285	0.020	0.562	0.002	0.023	0.038
33. Pertaining to Other Hobbies/Interests	Pearson's r	0.121	0.139	-0.129	-0.054	0.126	0.060	0.038	0.154	0.063	-0.172	-0.084	0.029	0.044	0.201	-0.058	0.247	0.031	-0.063
	p-value	0.397	0.332	0.366	0.708	0.378	0.675	0.790	0.282	0.661	0.227	0.559	0.842	0.759	0.156	0.685	0.081	0.828	0.661

Variable		Profile Picture of Owner	Anonymity of profile owner	Posts	Followers	Following	Bio word count	Anonymity in Bio	Location specificity	Links/info about other SNS in Bio	Self-images/selfies	Images of self with others	Images of only others	Number of unique others across posts	Number of images without people	Number of images with animals	Number of images outdoors	Number of photos of inanimate objects	Smiling
34. Pertaining to Religion	Pearson's r	-0.003	0.154	-0.020	-0.144	-0.090	-0.039	0.118	0.117	-0.177	-0.213	0.192	0.011	-0.056	0.042	-0.066	-0.004	-0.097	0.222
	p-value	0.986	0.280	0.888	0.313	0.532	0.788	0.409	0.415	0.214	0.133	0.177	0.939	0.698	0.768	0.644	0.975	0.497	0.118
35. Pertaining to Politics	Pearson's r	-0.035	-0.140	0.517***	0.263	0.043	0.041	0.013	0.090	0.005	-0.004	-0.164	0.146	-0.068	0.087	0.170	-0.206	0.012	-0.194
	p-value	0.805	0.327	< .001	0.062	0.763	0.773	0.930	0.531	0.974	0.976	0.249	0.308	0.635	0.545	0.233	0.148	0.935	0.173

* p < .05, ** p < .01, *** p < .001

Pearson's Correlations

Variable		Positive facial expression	Neutral facial expression	Negative facial expression	Dominant facial expression/pose	Attractive	Neat	Posed	Candid	Pertaining to Academics	Pertaining to Work	Pertaining to Movies/TV	Pertaining to Music	Pertaining to Art	Pertaining to Sports/Fitness	Pertaining to Other Hobbies/Interests	Pertaining to Religion	Pertaining to Politics
20. Neutral facial expression	Pearson's r	-0.853***	—															
	p-value	< .001	—															
21. Negative facial expression	Pearson's r	-0.414**	0.394**	—														
	p-value	0.003	0.004	—														
22. Dominant facial expression/pose	Pearson's r	-0.247	0.441**	0.266	—													
	p-value	0.081	0.001	0.059	—													
23. Attractive	Pearson's r	0.493***	-0.317*	-0.054	0.286*	—												
	p-value	< .001	0.024	0.708	0.042	—												
24. Neat	Pearson's r	0.645***	-0.574***	-0.194	0.017	0.657***	—											
	p-value	< .001	< .001	0.174	0.904	< .001	—											
25. Posed	Pearson's r	0.491***	-0.364**	-0.149	0.231	0.533***	0.471***	—										
	p-value	< .001	0.009	0.295	0.103	< .001	< .001	—										
26. Candid	Pearson's r	0.007	0.022	0.138	0.135	0.068	0.133	-0.354*	—									
	p-value	0.959	0.880	0.334	0.346	0.636	0.353	0.011	—									
27. Pertaining to Academics	Pearson's r	-0.139	0.147	0.016	0.043	0.063	-0.046	0.132	0.124	—								
	p-value	0.332	0.304	0.912	0.763	0.660	0.749	0.354	0.387	—								
28. Pertaining to Work	Pearson's r	-0.103	0.031	0.121	-0.210	-0.029	-0.192	-0.151	-0.091	0.139	—							
	p-value	0.471	0.830	0.398	0.138	0.837	0.176	0.290	0.524	0.330	—							
29. Pertaining to Movies/TV	Pearson's r	-0.362**	0.150	0.321*	-0.093	-0.464***	-0.350*	-0.224	-0.210	-0.269	0.144	—						
	p-value	0.009	0.293	0.022	0.515	< .001	0.012	0.115	0.140	0.056	0.312	—						
30. Pertaining to Music	Pearson's r	-0.153	0.243	-0.008	-0.003	-0.080	-0.390**	-0.227	-0.112	-0.165	-0.010	-0.021	—					
	p-value	0.283	0.086	0.954	0.981	0.575	0.005	0.110	0.432	0.249	0.943	0.886	—					
31. Pertaining to Art	Pearson's r	-0.225	0.193	0.036	-0.112	-0.319*	-0.380**	-0.265	0.021	-0.110	0.226	0.212	0.339*	—				
	p-value	0.112	0.175	0.802	0.436	0.023	0.006	0.060	0.886	0.444	0.110	0.136	0.015	—				
32. Pertaining to Sports/Fitness	Pearson's r	0.311*	-0.314*	-0.282*	0.204	0.278*	0.266	0.059	0.469***	0.142	-0.152	-0.217	-0.279*	-0.153	—			
	p-value	0.026	0.025	0.045	0.150	0.048	0.060	0.679	< .001	0.322	0.286	0.125	0.048	0.284	—			

Pearson's Correlations

Variable		Positive facial expression	Neutral facial expression	Negative facial expression	Dominant facial expression/pose	Attractive	Neat	Posed	Candid	Pertaining to Academics	Pertaining to Work	Pertaining to Movies/TV	Pertaining to Music	Pertaining to Art	Pertaining to Sports/Fitness	Pertaining to Other Hobbies/Interests	Pertaining to Religion	Pertaining to Politics
33. Pertaining to Other Hobbies/Interests	Pearson's r	-0.077	-0.041	-0.177	-0.098	-0.204	-0.102	-0.022	-0.228	-0.138	0.217	0.364**	-0.287*	0.157	-0.090	—		
	p-value	0.589	0.773	0.214	0.493	0.151	0.475	0.876	0.108	0.335	0.127	0.009	0.041	0.270	0.531	—		
34. Pertaining to Religion	Pearson's r	0.189	-0.241	-0.045	-0.202	-0.018	0.178	0.156	-0.126	0.121	-0.166	-0.109	-0.182	-0.129	-0.091	-0.142	—	
	p-value	0.183	0.088	0.755	0.156	0.902	0.212	0.273	0.378	0.396	0.244	0.445	0.201	0.368	0.525	0.319	—	
35. Pertaining to Politics	Pearson's r	-0.240	0.151	0.278*	-0.110	-0.170	-0.149	-0.204	0.132	0.006	0.053	0.115	-0.053	0.220	-0.041	-0.216	-0.067	—
	p-value	0.089	0.290	0.049	0.441	0.234	0.298	0.152	0.357	0.968	0.714	0.422	0.713	0.122	0.774	0.129	0.640	—

* p < .05, ** p < .01, *** p < .001

Table B2

Twitter Cue Correlation Table

Correlation

Pearson's Correlations

Variable		Profile Picture	Anonymity of profile owner	Profile Format Type	Posts	Followers	Following	Likes	Banner photo presence	Profile owner name specificity	Username anonymity - name info	Username anaonymity - other info	Bio word count	Bio emoji count (including name)	Anonymity in Bio	Personalness of Bio	Location specificity	Links/info about other SNS in Bio	Months on Twitter
1. Profile Picture	Pearson's r	—																	
	p-value	—																	
2. Anonymity of profile owner	Pearson's r	0.726***	—																
	p-value	< .001	—																
3. Profile Format Type	Pearson's r	-0.124	-0.152	—															
	p-value	0.416	0.318	—															
4. Posts	Pearson's r	-0.126	-0.107	-0.328*	—														
	p-value	0.410	0.483	0.028	—														
5. Followers	Pearson's r	-0.220	-0.017	0.227	0.390**	—													
	p-value	0.146	0.911	0.135	0.008	—													
6. Following	Pearson's r	-0.098	-0.096	-5.437×10^{-4}	0.561***	0.533***	—												
	p-value	0.523	0.529	0.997	< .001	< .001	—												
7. Likes	Pearson's r	-0.037	0.015	-0.145	0.524***	0.084	0.039	—											
	p-value	0.811	0.922	0.342	< .001	0.585	0.800	—											
8. Banner photo presence	Pearson's r	0.230	0.088	0.263	-0.211	0.096	-0.054	-0.094	—										
	p-value	0.129	0.567	0.081	0.165	0.530	0.723	0.541	—										
9. Profile owner name specificity	Pearson's r	-0.127	-0.123	0.055	0.072	0.061	-0.100	0.044	-0.186	—									
	p-value	0.404	0.422	0.718	0.638	0.693	0.512	0.774	0.221	—									
10. Username anonymity - name info	Pearson's r	-0.204	-0.247	0.079	0.153	-0.319*	-0.143	0.285	-0.063	0.079	—								
	p-value	0.180	0.102	0.606	0.316	0.033	0.350	0.058	0.679	0.606	—								
11. Username anaonymity - other info	Pearson's r	0.040	0.115	-0.324*	0.106	0.167	0.145	0.047	0.047	0.144	0.002	—							
	p-value	0.793	0.452	0.030	0.487	0.272	0.342	0.759	0.759	0.346	0.987	—							
12. Bio word count	Pearson's r	0.221	0.101	-0.122	0.061	-0.082	0.228	-0.129	-0.023	-0.183	0.142	4.639×10^{-4}	—						
	p-value	0.144	0.509	0.424	0.693	0.590	0.132	0.398	0.883	0.228	0.352	0.998	—						
13. Bio emoji count (including name)	Pearson's r	0.173	0.243	-0.097	0.375*	0.136	0.381**	0.032	0.103	0.116	0.124	0.094	0.259	—					
	p-value	0.256	0.107	0.527	0.011	0.374	0.010	0.834	0.502	0.447	0.417	0.538	0.085	—					
14. Anonymity in Bio	Pearson's r	0.194	0.177	0.024	-0.277	-0.223	-0.506***	0.044	0.244	-0.095	0.135	0.012	-0.296*	-0.324*	—				
	p-value	0.202	0.246	0.874	0.066	0.140	< .001	0.774	0.106	0.537	0.376	0.940	0.048	0.030	—				
15. Personalness of Bio	Pearson's r	-0.115	-0.053	-0.019	-0.005	0.028	-0.345*	0.169	0.013	0.173	-0.075	0.031	-0.840***	-0.374*	0.524***	—			
	p-value	0.452	0.727	0.902	0.973	0.853	0.020	0.268	0.931	0.255	0.623	0.838	< .001	0.011	< .001	—			
16. Location specificity	Pearson's r	0.073	0.115	0.054	-0.107	-0.014	-0.311*	-0.077	-0.026	-0.011	0.078	-0.068	-0.074	-0.148	0.319*	0.244	—		
	p-value	0.634	0.450	0.722	0.485	0.925	0.038	0.615	0.866	0.941	0.610	0.657	0.628	0.331	0.032	0.106	—		
17. Links/info about other SNS in Bio	Pearson's r	-0.198	-0.196	-0.107	0.085	0.221	0.092	-0.091	-0.072	0.180	-0.023	0.111	0.188	-0.074	-0.388**	-0.163	0.043	—	
	p-value	0.193	0.196	0.484	0.577	0.145	0.547	0.551	0.639	0.237	0.878	0.466	0.217	0.630	0.008	0.283	0.778	—	
18. Months on Twitter	Pearson's r	-0.146	-0.053	0.098	0.323*	0.331*	0.280	0.195	0.121	-0.021	0.332*	0.370*	0.062	0.100	-0.091	-0.054	-0.100	0.161	—
	p-value	0.338	0.728	0.523	0.030	0.026	0.062	0.200	0.428	0.894	0.026	0.012	0.685	0.514	0.552	0.722	0.515	0.292	—
19. Birthday	Pearson's r	0.161	0.320*	0.018	-0.017	0.115	-0.057	-0.223	0.188	-0.216	-0.065	-0.091	-0.005	0.257	-0.006	0.025	0.238	0.105	-0.085
	p-value	0.290	0.032	0.909	0.911	0.452	0.709	0.140	0.215	0.155	0.672	0.553	0.973	0.088	0.970	0.873	0.116	0.494	0.578

Pearson's Correlations

Variable		Profile Picture	Anonymity of profile owner	Profile Format Type	Posts	Followers	Following	Likes	Banner photo presence	Profile owner name specificity	Username anonymity - name info	Username anaonymity - other info	Bio word count	Bio emoji count (including name)	Anonymity in Bio	Personalness of Bio	Location specificity	Links/info about other SNS in Bio	Months on Twitter
20. Media Total	Pearson's r	-0.095	-0.114	-0.226	0.859***	0.420**	0.679***	0.225	-0.143	-0.027	0.083	0.073	0.059	0.531***	-0.324*	-0.049	-0.101	0.048	0.205
	p-value	0.534	0.456	0.136	< .001	0.004	< .001	0.137	0.348	0.862	0.587	0.633	0.698	< .001	0.030	0.752	0.509	0.755	0.177
21. Pinned tweet	Pearson's r	0.036	0.076	-0.095	-0.206	-0.089	-0.142	-0.206	0.255	-0.195	0.081	-0.123	-0.085	-0.247	0.249	0.033	0.116	-0.074	0.122
	p-value	0.813	0.621	0.535	0.174	0.561	0.354	0.174	0.091	0.200	0.596	0.420	0.577	0.102	0.099	0.828	0.447	0.629	0.424
22. Number of images in feed	Pearson's r	0.006	0.055	0.167	-0.004	0.237	0.015	-0.062	0.283	-0.070	-0.029	-0.113	0.136	0.121	-0.191	-0.201	0.118	0.173	0.162
	p-value	0.971	0.719	0.273	0.979	0.118	0.922	0.687	0.060	0.650	0.850	0.460	0.373	0.427	0.209	0.185	0.441	0.257	0.289
23. Number of videos	Pearson's r	0.104	0.290	-0.004	-0.029	0.272	-0.061	0.079	0.039	-0.185	-0.300*	0.101	0.117	0.074	-0.067	-0.198	0.145	0.103	0.130
	p-value	0.498	0.053	0.979	0.851	0.071	0.693	0.604	0.801	0.224	0.045	0.509	0.445	0.627	0.661	0.193	0.341	0.500	0.396
24. Self-images/selfies	Pearson's r	-0.200	0.058	-0.131	0.113	0.199	-0.038	-0.075	-0.176	0.143	-0.112	0.113	-0.005	-0.008	-0.069	0.056	0.000	0.204	0.148
	p-value	0.187	0.705	0.392	0.461	0.189	0.802	0.622	0.248	0.349	0.465	0.460	0.976	0.959	0.654	0.717	1.000	0.180	0.333
25. Images of self with others	Pearson's r	-0.090	0.309*	-0.247	0.073	0.270	0.037	-0.056	-0.192	-0.196	-0.397**	0.118	-0.039	-0.025	-0.095	0.034	0.006	0.083	-0.004
	p-value	0.554	0.039	0.102	0.633	0.073	0.811	0.714	0.207	0.196	0.007	0.442	0.799	0.873	0.535	0.822	0.969	0.589	0.981
26. Images of only others (seemingly friends/acquaintances)	Pearson's r	-0.058	-0.089	-0.025	-0.119	0.100	0.099	-0.101	0.250	-0.114	-0.228	0.082	-0.080	-0.101	-0.004	0.058	0.065	0.115	-0.135
	p-value	0.705	0.560	0.869	0.436	0.514	0.517	0.511	0.097	0.456	0.133	0.593	0.602	0.508	0.978	0.707	0.671	0.453	0.376
27. Diverse others	Pearson's r	-0.133	0.094	-0.019	0.107	0.387**	0.254	-0.055	-0.094	-0.242	-0.323*	0.114	0.104	0.037	-0.048	-0.115	0.122	0.225	0.060
	p-value	0.384	0.539	0.899	0.485	0.009	0.093	0.721	0.538	0.109	0.031	0.455	0.496	0.812	0.755	0.453	0.424	0.137	0.693
28. Images of only others (celebrities/memes)	Pearson's r	0.044	0.170	0.110	0.166	0.266	0.102	0.157	0.179	-0.170	0.046	0.048	0.230	0.267	-0.161	-0.333*	-0.027	-0.116	0.332*
	p-value	0.775	0.263	0.472	0.274	0.077	0.506	0.304	0.240	0.265	0.766	0.756	0.129	0.077	0.290	0.025	0.858	0.448	0.026
29. Number of images without people	Pearson's r	0.264	0.095	-0.329*	0.286	-0.149	0.117	0.201	-0.174	-0.074	0.277	-0.059	0.357*	0.129	-0.194	-0.239	-0.185	0.178	0.198
	p-value	0.079	0.537	0.027	0.057	0.327	0.446	0.185	0.252	0.627	0.066	0.698	0.016	0.397	0.201	0.113	0.224	0.241	0.193
30. Original tweets in screenshot	Pearson's r	0.039	-0.121	0.124	-0.009	-0.221	0.174	-0.025	-0.147	-0.022	0.128	-0.318*	0.201	0.029	-0.120	-0.207	0.021	-0.140	-0.311*
	p-value	0.802	0.427	0.417	0.954	0.144	0.253	0.873	0.336	0.887	0.403	0.033	0.186	0.852	0.432	0.173	0.890	0.361	0.038
31. Replies to original tweets (total)	Pearson's r	-0.052	-0.119	-0.136	0.112	0.139	0.119	-0.034	-0.122	0.029	-0.297*	0.089	0.107	0.160	-0.400**	-0.096	-0.086	0.274	-0.149
	p-value	0.737	0.438	0.375	0.464	0.363	0.437	0.827	0.425	0.849	0.047	0.563	0.482	0.295	0.006	0.532	0.573	0.069	0.328
32. Retweets on original tweets (total)	Pearson's r	-0.060	0.011	-0.104	0.011	0.053	-0.096	-0.033	-0.072	0.265	-0.143	0.033	0.004	0.030	-0.324*	-0.058	-0.211	0.311*	-0.022
	p-value	0.694	0.945	0.496	0.943	0.727	0.532	0.831	0.639	0.078	0.348	0.831	0.977	0.847	0.030	0.704	0.165	0.037	0.888
33. Likes on original tweets (total)	Pearson's r	-0.065	-0.026	-0.100	-0.027	0.035	-0.116	-0.033	-0.084	0.280	-0.166	0.039	-0.011	0.003	-0.298*	-0.014	-0.202	0.330*	-0.068
	p-value	0.674	0.864	0.511	0.860	0.819	0.447	0.828	0.586	0.062	0.276	0.802	0.942	0.985	0.047	0.929	0.183	0.027	0.656
34. Retweets in screenshot	Pearson's r	-0.042	0.116	-0.107	0.043	0.241	-0.148	0.056	0.112	0.047	-0.135	0.335*	-0.186	0.008	0.089	0.201	-0.034	0.155	0.303*
	p-value	0.784	0.450	0.482	0.781	0.111	0.331	0.714	0.463	0.760	0.378	0.024	0.222	0.959	0.560	0.185	0.824	0.309	0.043
35. Under 10	Pearson's r	-0.227	-0.111	-0.044	-0.126	-0.031	0.043	-0.141	0.049	-0.043	-0.214	0.052	0.103	-0.206	-0.115	-0.128	0.061	0.146	-0.191
	p-value	0.133	0.466	0.773	0.409	0.839	0.778	0.356	0.750	0.781	0.158	0.733	0.502	0.174	0.453	0.402	0.692	0.338	0.208
36. 10-100	Pearson's r	-0.217	-0.029	-0.088	-0.234	-0.109	-0.155	-0.152	0.201	-0.035	-0.179	0.123	-0.141	-0.015	-0.164	0.059	-0.255	0.114	-0.102
	p-value	0.151	0.851	0.565	0.122	0.476	0.309	0.318	0.186	0.818	0.240	0.422	0.356	0.923	0.283	0.699	0.091	0.455	0.504
37. 100-1k	Pearson's r	-0.053	0.045	-0.054	0.114	0.054	-0.149	0.261	0.119	0.158	0.150	0.130	-0.151	0.209	0.165	0.160	-0.224	-0.179	0.303*
	p-value	0.729	0.771	0.725	0.454	0.726	0.328	0.083	0.437	0.301	0.325	0.396	0.323	0.168	0.278	0.294	0.138	0.239	0.043
38. 1k-10k	Pearson's r	0.157	0.190	-0.097	0.269	0.088	-0.030	0.322*	-0.180	0.047	0.262	0.170	0.221	0.246	0.009	-0.158	0.168	0.209	0.380*
	p-value	0.302	0.212	0.527	0.074	0.564	0.846	0.031	0.237	0.760	0.083	0.264	0.145	0.103	0.951	0.301	0.270	0.168	0.010
39. 10k-100k	Pearson's r	0.228	0.187	-0.025	0.105	0.332*	0.009	-0.091	0.012	-0.011	-0.233	0.139	-0.287	-0.121	0.141	0.326*	0.104	0.100	0.151
	p-value	0.133	0.218	0.868	0.494	0.026	0.953	0.550	0.939	0.943	0.123	0.362	0.056	0.427	0.357	0.029	0.496	0.511	0.322

Pearson's Correlations

Variable		Profile Picture	Anonymity of profile owner	Profile Format Type	Posts	Followers	Following	Likes	Banner photo presence	Profile owner name specificity	Username anonymity - name info	Username anaonymity - other info	Bio word count	Bio emoji count (including name)	Anonymity in Bio	Personalness of Bio	Location specificity	Links/info about other SNS in Bio	Months on Twitter
40. 100k+	Pearson's r	0.074	-0.036	0.022	-0.196	-0.034	-0.094	-0.122	0.015	-0.177	-0.034	0.098	0.007	0.022	0.142	0.010	0.078	-0.165	-0.067
	p-value	0.627	0.813	0.888	0.196	0.826	0.540	0.423	0.925	0.245	0.825	0.522	0.966	0.888	0.353	0.950	0.610	0.278	0.662
41. Swear words	Pearson's r	-0.004	0.042	-0.261	0.148	-0.117	-0.031	0.101	-0.278	0.174	0.181	0.035	-0.306*	0.035	0.173	0.258	0.082	-0.054	-0.174
	p-value	0.980	0.785	0.083	0.333	0.446	0.840	0.508	0.064	0.253	0.234	0.818	0.041	0.820	0.257	0.087	0.593	0.726	0.253
42. Sexually explicit words	Pearson's r	-0.025	-0.103	-0.016	0.320*	0.002	0.120	0.124	-0.176	0.402**	0.433**	0.085	0.124	0.274	-0.054	-0.044	0.037	0.093	0.074
	p-value	0.870	0.502	0.915	0.032	0.992	0.432	0.417	0.249	0.006	0.003	0.580	0.418	0.068	0.727	0.775	0.811	0.542	0.630
43. Emojis	Pearson's r	-0.022	0.070	-0.009	-0.082	0.082	-0.153	-0.038	0.136	0.330*	0.073	0.174	-0.082	0.092	0.037	0.099	0.246	0.227	0.051
	p-value	0.888	0.650	0.954	0.591	0.591	0.316	0.807	0.372	0.027	0.635	0.252	0.594	0.546	0.807	0.517	0.103	0.133	0.739
44. Initialisms	Pearson's r	-0.129	-0.307*	-0.272	0.144	-0.073	-0.117	0.105	-0.172	0.178	0.238	0.156	-0.015	-0.060	0.164	0.138	0.067	0.083	0.092
	p-value	0.399	0.040	0.071	0.344	0.634	0.442	0.493	0.258	0.243	0.116	0.308	0.922	0.696	0.280	0.366	0.660	0.589	0.549
45. Exaggerated spellings (seemingly purposeful)	Pearson's r	-0.048	-0.085	-0.202	0.335*	-0.014	0.031	0.071	-0.256	0.012	0.292	0.066	-0.062	-0.061	0.198	0.203	0.073	0.101	-0.017
	p-value	0.755	0.581	0.183	0.024	0.929	0.842	0.643	0.090	0.937	0.052	0.669	0.688	0.693	0.192	0.181	0.633	0.508	0.912
46. Misspellings (seemingly accidental)	Pearson's r	0.189	0.026	0.021	0.026	-0.072	0.029	-0.070	0.138	0.169	-0.164	-0.426**	0.146	0.049	-0.124	-0.215	-0.294	0.075	-0.114
	p-value	0.214	0.868	0.893	0.863	0.639	0.851	0.648	0.366	0.268	0.282	0.003	0.339	0.751	0.417	0.156	0.050	0.626	0.455
47. Smiling	Pearson's r	-0.225	0.049	-0.258	0.196	0.271	0.390**	-0.090	-0.106	-0.175	-0.304*	0.181	0.008	-0.058	-0.249	-0.065	-0.154	-0.017	0.135
	p-value	0.137	0.749	0.087	0.196	0.071	0.008	0.555	0.490	0.250	0.042	0.233	0.960	0.704	0.099	0.673	0.314	0.911	0.376
48. Positive facial expression	Pearson's r	-0.287	-0.001	-0.154	0.200	0.303*	0.364*	-0.065	-0.158	-0.114	-0.221	0.103	0.007	-0.037	-0.254	-0.039	-0.121	-0.002	0.191
	p-value	0.056	0.995	0.313	0.188	0.043	0.014	0.674	0.299	0.455	0.145	0.501	0.962	0.811	0.092	0.799	0.430	0.988	0.209
49. Neutral facial expression	Pearson's r	-0.257	-0.367*	0.378*	-0.273	-0.096	-0.395**	-0.040	-0.007	0.213	0.237	-0.144	-0.321*	-0.322*	0.168	0.263	0.093	0.117	-0.044
	p-value	0.088	0.013	0.010	0.070	0.529	0.007	0.792	0.965	0.159	0.117	0.344	0.031	0.031	0.270	0.081	0.543	0.445	0.772
50. Negative facial expression	Pearson's r	-0.291	-0.348*	0.015	-0.073	-0.123	-0.229	0.038	-0.228	0.175	0.229	-0.185	-0.185	-0.246	0.137	0.241	0.030	-0.070	-0.155
	p-value	0.052	0.019	0.924	0.634	0.422	0.130	0.802	0.133	0.251	0.130	0.224	0.225	0.103	0.371	0.110	0.847	0.647	0.308
51. Dominant facial expression/pose	Pearson's r	-0.315*	-0.230	0.181	-0.181	0.014	-0.182	-0.096	0.061	-0.105	0.082	-0.088	-0.161	-0.263	0.078	0.044	0.023	0.122	-0.180
	p-value	0.035	0.129	0.234	0.235	0.928	0.231	0.532	0.691	0.491	0.593	0.565	0.291	0.081	0.612	0.774	0.883	0.425	0.237
52. Stylish	Pearson's r	-0.364*	-0.134	0.127	-0.049	0.434**	0.098	-0.147	-0.157	0.036	-0.157	0.102	-0.144	-0.160	-0.150	0.073	0.014	-0.007	0.255
	p-value	0.014	0.381	0.405	0.748	0.003	0.521	0.334	0.304	0.812	0.304	0.507	0.347	0.293	0.326	0.632	0.930	0.964	0.091
53. Attractive	Pearson's r	-0.396**	-0.145	-0.052	0.044	0.401**	-0.019	-0.210	-0.172	0.245	-0.211	0.095	-0.109	-0.107	-0.080	0.140	0.126	0.116	0.137
	p-value	0.007	0.342	0.733	0.772	0.006	0.902	0.167	0.258	0.104	0.163	0.534	0.478	0.483	0.602	0.359	0.411	0.448	0.368
54. Neat	Pearson's r	-0.469**	-0.265	0.287	-0.092	0.304*	0.019	-0.226	-0.066	0.021	-0.130	-0.018	-0.172	-0.323*	-0.019	0.088	-0.049	0.065	0.198
	p-value	0.001	0.079	0.056	0.550	0.042	0.900	0.135	0.669	0.891	0.396	0.905	0.259	0.031	0.904	0.566	0.750	0.672	0.193
55. Posed	Pearson's r	-0.588***	-0.409**	0.158	0.048	0.357*	0.156	-0.081	-0.062	0.114	-0.150	0.043	-0.336*	-0.299*	-0.190	0.205	-0.058	0.007	0.141
	p-value	< .001	0.005	0.298	0.754	0.016	0.305	0.598	0.688	0.456	0.324	0.778	0.024	0.046	0.211	0.177	0.706	0.963	0.355
56. Candid	Pearson's r	-0.202	-0.012	-0.175	-0.080	-0.096	-0.131	0.105	-0.177	-0.214	-0.022	-6.374×10^{-4}	0.085	-0.108	0.015	-0.136	-0.018	0.172	-0.059
	p-value	0.183	0.935	0.250	0.602	0.530	0.392	0.494	0.245	0.159	0.886	0.997	0.577	0.479	0.923	0.373	0.908	0.257	0.698
57. General positivity	Pearson's r	-0.085	0.089	-0.135	0.011	0.340*	0.175	-0.139	0.128	-0.148	-0.322*	0.242	0.176	0.167	-0.157	-0.231	0.029	0.210	-0.022
	p-value	0.578	0.560	0.377	0.942	0.022	0.249	0.363	0.401	0.331	0.031	0.110	0.247	0.274	0.303	0.126	0.851	0.167	0.884
58. Optimism	Pearson's r	-0.162	0.053	0.093	0.014	0.332*	0.157	-0.174	0.047	-0.024	-0.142	0.091	0.110	0.191	-0.029	-0.154	0.107	0.158	-0.048
	p-value	0.287	0.729	0.545	0.929	0.026	0.303	0.252	0.757	0.875	0.352	0.550	0.471	0.208	0.850	0.312	0.484	0.300	0.755
59. Achievement	Pearson's r	-0.186	0.023	0.027	0.048	0.345*	0.283	-0.109	0.142	-0.363*	-0.260	0.018	0.197	0.141	-0.189	-0.322*	0.055	0.132	-0.043
	p-value	0.220	0.881	0.860	0.753	0.020	0.059	0.477	0.353	0.014	0.085	0.905	0.194	0.357	0.213	0.031	0.721	0.389	0.780

Pearson's Correlations

Variable		Profile Picture	Anonymity of profile owner	Profile Format Type	Posts	Followers	Following	Likes	Banner photo presence	Profile owner name specificity	Username anonymity - name info	Username anaonymity - other info	Bio word count	Bio emoji count (including name)	Anonymity in Bio	Personalness of Bio	Location specificity	Links/info about other SNS in Bio	Months on Twitter
60. Gratitude	Pearson's r	-0.137	-4.670×10^{-4}	0.050	-0.123	0.058	0.102	-0.158	0.033	-0.216	-0.195	-0.016	0.200	0.134	-0.162	-0.338*	-0.132	0.158	-0.199
	p-value	0.371	0.998	0.745	0.420	0.705	0.504	0.299	0.827	0.154	0.200	0.916	0.188	0.381	0.289	0.023	0.388	0.301	0.190
61. General negativity	Pearson's r	-0.087	-0.232	0.147	-0.142	-0.323*	-0.173	0.047	-0.159	0.027	0.390**	-0.227	-0.281	-0.177	0.135	0.269	-0.005	-0.224	0.060
	p-value	0.569	0.126	0.336	0.351	0.031	0.256	0.761	0.296	0.859	0.008	0.133	0.062	0.245	0.378	0.073	0.972	0.138	0.694
62. Stress/Anxiety	Pearson's r	-0.067	-0.067	0.069	-0.192	-0.225	-0.262	-0.159	-0.124	-0.310*	0.247	-0.203	-0.281	-0.346*	0.383**	0.351*	0.294	-0.149	0.050
	p-value	0.660	0.661	0.653	0.206	0.137	0.082	0.296	0.416	0.038	0.102	0.180	0.062	0.020	0.009	0.018	0.050	0.328	0.745
63. Sadness	Pearson's r	0.127	0.018	0.021	-0.086	-0.212	-0.211	-0.064	-0.240	0.065	0.275	0.101	-0.120	-0.076	0.335*	0.292	0.053	-0.122	-0.045
	p-value	0.404	0.906	0.890	0.573	0.162	0.164	0.674	0.112	0.672	0.068	0.507	0.432	0.622	0.025	0.051	0.728	0.426	0.770
64. Anger	Pearson's r	0.106	-0.079	0.223	-0.037	-0.267	-0.066	0.206	0.010	-0.076	0.311*	-0.319*	-0.192	-0.123	0.122	0.151	-0.050	-0.297*	-0.032
	p-value	0.488	0.606	0.141	0.808	0.077	0.667	0.175	0.946	0.621	0.038	0.033	0.205	0.419	0.424	0.322	0.743	0.047	0.836
65. General amount of humor	Pearson's r	0.298*	0.194	-0.058	-0.064	-0.149	-0.112	-0.057	-0.221	0.015	0.017	-0.150	0.049	0.030	0.068	0.045	0.181	-0.026	-0.130
	p-value	0.047	0.201	0.706	0.678	0.327	0.465	0.710	0.145	0.921	0.914	0.325	0.747	0.845	0.658	0.771	0.235	0.863	0.396
66. Memes	Pearson's r	0.552***	0.386**	-0.172	-0.106	-0.357*	-0.224	-0.065	-0.061	-0.224	0.128	-0.265	0.291	0.090	0.211	-0.099	0.239	-0.054	-0.223
	p-value	< .001	0.009	0.259	0.488	0.016	0.139	0.672	0.688	0.139	0.401	0.078	0.052	0.555	0.163	0.518	0.114	0.727	0.141
67. Sarcasm	Pearson's r	0.133	-0.005	0.252	-0.176	-0.201	-0.181	-0.165	-0.230	-0.041	0.131	-0.394**	0.094	-0.248	0.238	0.048	0.163	-0.257	-0.253
	p-value	0.384	0.975	0.095	0.246	0.186	0.234	0.278	0.128	0.789	0.391	0.007	0.540	0.101	0.115	0.752	0.286	0.088	0.094
68. Mentions of Specifc Others Unknown	Pearson's r	0.213	0.190	0.437**	-0.175	-0.137	-0.121	-0.027	0.443**	-0.221	0.126	-0.370*	-0.045	0.176	0.204	-0.056	-0.090	-0.281	0.190
	p-value	0.161	0.211	0.003	0.251	0.369	0.429	0.860	0.002	0.145	0.410	0.012	0.769	0.247	0.179	0.715	0.558	0.061	0.211
69. Mentions of Specific Others Known	Pearson's r	0.066	-0.037	-0.207	-0.191	-0.240	-0.154	-0.187	0.221	0.020	-0.200	0.148	0.048	-0.035	-0.023	-0.031	0.130	0.201	-0.439**
	p-value	0.668	0.807	0.171	0.209	0.113	0.314	0.219	0.144	0.899	0.188	0.330	0.754	0.818	0.878	0.840	0.395	0.187	0.003
70. Mentions of Generic Others	Pearson's r	0.031	-0.088	0.331*	0.032	4.245×10^{-4}	0.308*	-0.120	0.066	-0.182	0.179	-0.420**	0.097	0.207	-0.067	-0.118	-0.122	-0.074	-0.037
	p-value	0.842	0.567	0.027	0.835	0.998	0.040	0.431	0.669	0.231	0.239	0.004	0.527	0.172	0.662	0.441	0.425	0.630	0.808
71. Pertaining to non-romantic relationships	Pearson's r	0.030	0.090	0.059	-0.022	0.014	0.052	-0.162	0.069	-0.414**	0.040	-0.279	0.147	0.229	-0.122	-0.163	0.003	0.064	-0.133
	p-value	0.846	0.555	0.699	0.885	0.925	0.737	0.288	0.653	0.005	0.795	0.064	0.334	0.130	0.426	0.286	0.982	0.677	0.385
72. Pertaining to romantic relationships	Pearson's r	-0.228	-0.080	0.128	-0.108	-0.025	-0.048	-0.021	-0.266	0.489***	-0.100	0.177	-0.150	0.079	-0.095	0.091	-0.140	0.065	-0.182
	p-value	0.132	0.600	0.401	0.480	0.870	0.753	0.892	0.077	< .001	0.515	0.244	0.327	0.608	0.536	0.553	0.360	0.670	0.232
73. Sexual content	Pearson's r	0.135	0.104	0.080	0.168	-0.119	-0.048	0.346*	0.078	0.363*	0.397**	0.170	0.161	0.378*	-0.011	-0.066	-0.079	0.061	0.143
	p-value	0.378	0.496	0.602	0.271	0.437	0.755	0.020	0.612	0.014	0.007	0.263	0.292	0.010	0.941	0.664	0.605	0.690	0.350
74. Pertaining to Academics	Pearson's r	-0.178	-0.016	-0.214	-0.011	-0.037	0.036	-0.124	-0.102	-0.320*	0.041	0.136	-0.380**	-0.023	0.014	0.215	0.072	-0.063	-0.150
	p-value	0.242	0.919	0.159	0.942	0.809	0.817	0.417	0.505	0.032	0.790	0.372	0.010	0.881	0.929	0.156	0.636	0.683	0.324
75. Pertaining to Work	Pearson's r	-0.090	-0.037	0.105	0.095	0.108	0.319*	-0.088	0.004	-1.076×10^{-10}	0.116	0.094	-0.020	0.159	-0.273	-0.085	-0.283	0.116	0.261
	p-value	0.554	0.808	0.493	0.537	0.479	0.033	0.567	0.977	1.000	0.448	0.541	0.896	0.296	0.069	0.579	0.060	0.449	0.083
76. Pertaining to Movies/TV	Pearson's r	0.267	0.135	0.142	-0.042	0.093	0.094	-0.110	0.407**	0.088	-0.090	-0.005	0.326*	0.163	-0.053	-0.305*	-0.045	0.106	0.105
	p-value	0.076	0.377	0.354	0.783	0.543	0.538	0.473	0.006	0.563	0.558	0.975	0.029	0.286	0.730	0.041	0.771	0.488	0.492
77. Pertaining to Music	Pearson's r	0.205	0.274	-0.153	0.087	0.002	-0.106	0.206	0.011	0.452**	0.037	0.061	-0.067	0.166	0.092	0.124	0.112	0.051	0.191
	p-value	0.177	0.068	0.315	0.571	0.989	0.487	0.174	0.942	0.002	0.810	0.692	0.662	0.274	0.548	0.416	0.463	0.741	0.210
78. Pertaining to Art	Pearson's r	0.580***	0.495***	-0.141	-0.018	-0.156	-0.016	-0.063	0.111	0.135	-0.010	0.088	0.366*	0.375*	-0.022	-0.149	0.103	0.112	-0.053
	p-value	< .001	< .001	0.357	0.906	0.306	0.915	0.681	0.469	0.376	0.950	0.565	0.014	0.011	0.888	0.328	0.501	0.464	0.730
79. Pertaining to Sports	Pearson's r	-0.219	-0.038	0.061	-0.022	0.257	0.047	0.118	0.023	-0.277	-0.154	0.124	0.053	-0.027	0.033	-0.193	-0.026	0.062	0.015
	p-value	0.148	0.806	0.692	0.884	0.088	0.758	0.441	0.879	0.065	0.311	0.419	0.728	0.861	0.830	0.203	0.867	0.687	0.923

Pearson's Correlations

Variable		Profile Picture	Anonymity of profile owner	Profile Format Type	Posts	Followers	Following	Likes	Banner photo presence	Profile owner name specificity	Username anonymity - name info	Username anaonymity - other info	Bio word count	Bio emoji count (including name)	Anonymity in Bio	Personalness of Bio	Location specificity	Links/info about other SNS in Bio	Months on Twitter
80. Pertaining to Other Hobbies/Interests	Pearson's r	-0.092	-0.221	-0.037	0.331*	0.194	0.339*	0.077	-0.274	-0.089	-0.001	0.132	0.054	0.043	-0.444**	-0.158	-0.073	0.260	0.113
	p-value	0.546	0.145	0.809	0.027	0.201	0.023	0.617	0.069	0.562	0.993	0.387	0.726	0.779	0.002	0.299	0.635	0.085	0.460
81. Political content	Pearson's r	0.334*	0.118	0.269	-0.098	-0.146	0.240	-0.115	0.290	-0.343*	0.152	-0.381**	0.317*	0.099	-0.053	-0.244	-0.239	-0.190	0.084
	p-value	0.025	0.441	0.074	0.524	0.339	0.112	0.452	0.053	0.021	0.320	0.010	0.034	0.519	0.730	0.106	0.114	0.210	0.585
82. Religious content	Pearson's r	0.223	0.158	-0.180	-0.129	-0.162	-0.121	-0.065	-0.085	-0.253	-0.006	0.058	0.505***	-0.023	0.086	-0.267	0.077	0.004	-0.130
	p-value	0.140	0.299	0.236	0.397	0.287	0.429	0.671	0.578	0.094	0.967	0.703	< .001	0.878	0.575	0.076	0.617	0.978	0.396

* p < .05, ** p < .01, *** p < .001

Pearson's Correlations

Variable		Birthday	Media Total	Pinned tweet	Number of images in feed	Number of videos	Self-images/selfies	Images of self with others	Images of only others (seemingly friends/acquaintances)	Diverse others	Images of only others (celebrities/memes)	Number of images without people	Original tweets in screenshot	Replies to original tweets (total)	Retweets on original tweets (total)	Likes on original tweets (total)	Retweets in screenshot	Under 10
19. Birthday	Pearson's r	—																
	p-value	—																
20. Media Total	Pearson's r	0.151	—															
	p-value	0.323	—															
21. Pinned tweet	Pearson's r	0.021	-0.288	—														
	p-value	0.894	0.055	—														
22. Number of images in feed	Pearson's r	0.019	-0.033	0.096	—													
	p-value	0.902	0.830	0.529	—													
23. Number of videos	Pearson's r	0.138	-0.072	-0.149	0.323*	—												
	p-value	0.365	0.641	0.329	0.031	—												
24. Self-images/selfies	Pearson's r	-0.113	0.046	-0.204	0.016	0.132	—											
	p-value	0.460	0.766	0.179	0.919	0.386	—											
25. Images of self with others	Pearson's r	0.171	0.059	0.126	0.029	0.295*	0.397**	—										
	p-value	0.262	0.701	0.409	0.852	0.049	0.007	—										
26. Images of only others (seemingly friends/acquaintances)	Pearson's r	0.131	-0.060	0.066	0.424**	0.216	-0.016	0.166	—									
	p-value	0.391	0.697	0.664	0.004	0.153	0.915	0.275	—									
27. Diverse others	Pearson's r	0.143	0.172	-0.042	0.198	0.425**	0.269	0.672***	0.428**	—								
	p-value	0.349	0.260	0.782	0.193	0.004	0.074	< .001	0.003	—								
28. Images of only others (celebrities/memes)	Pearson's r	-0.041	0.118	-0.095	0.534***	0.462**	-0.035	-4.397×10^{-4}	-0.203	-0.095	—							
	p-value	0.788	0.442	0.535	< .001	0.001	0.818	0.998	0.182	0.536	—							
29. Number of images without people	Pearson's r	-0.076	0.128	0.002	0.196	0.109	-0.204	-0.260	-0.061	-0.127	0.048	—						
	p-value	0.619	0.402	0.989	0.196	0.477	0.178	0.084	0.689	0.404	0.755	—						
30. Original tweets in screenshot	Pearson's r	-0.117	0.010	-0.037	-0.321*	-0.489***	0.039	-0.281	-0.231	-0.308*	-0.228	-0.096	—					
	p-value	0.446	0.947	0.807	0.032	< .001	0.798	0.062	0.127	0.040	0.133	0.530	—					
31. Replies to original tweets (total)	Pearson's r	0.096	0.208	-0.433**	-0.033	-0.018	0.079	0.157	0.075	0.175	-0.100	0.009	0.192	—				
	p-value	0.528	0.170	0.003	0.827	0.907	0.606	0.302	0.623	0.249	0.515	0.952	0.206	—				
32. Retweets on original tweets (total)	Pearson's r	-0.192	0.023	-0.270	0.050	-0.043	0.370*	0.228	-0.050	-0.008	0.040	-0.031	0.007	0.562***	—			
	p-value	0.205	0.882	0.073	0.743	0.781	0.012	0.132	0.744	0.959	0.794	0.839	0.961	< .001	—			

Pearson's Correlations

Variable		Birthday	Media Total	Pinned tweet	Number of images in feed	Number of videos	Self-images/selfies	Images of self with others	Images of only others (seemingly friends/acquaintances)	Diverse others	Images of only others (celebrities/memes)	Number of images without people	Original tweets in screenshot	Replies to original tweets (total)	Retweets on original tweets (total)	Likes on original tweets (total)	Retweets in screenshot	Under 10
33. Likes on original tweets (total)	Pearson's r	-0.175	9.898×10^{-4}	-0.292	0.005	-0.094	0.333*	0.185	-0.061	-0.010	-0.030	-0.040	0.052	0.670***	0.968***	—		
	p-value	0.251	0.995	0.052	0.975	0.539	0.025	0.223	0.692	0.947	0.846	0.792	0.734	< .001	< .001	—		
34. Retweets in screenshot	Pearson's r	0.110	0.034	-0.099	0.317*	0.501***	-0.005	0.264	0.225	0.317*	0.244	0.091	-0.990***	-0.134	0.033	-0.008	—	
	p-value	0.473	0.823	0.518	0.034	< .001	0.974	0.080	0.137	0.034	0.107	0.553	< .001	0.381	0.829	0.957	—	
35. Under 10	Pearson's r	0.007	-0.177	0.055	0.169	0.004	-0.025	0.315*	0.522***	0.462**	-0.297*	-0.084	-0.185	0.083	0.034	0.016	0.183	—
	p-value	0.965	0.245	0.721	0.267	0.977	0.870	0.035	< .001	0.001	0.047	0.582	0.223	0.587	0.823	0.914	0.229	—
36. 10-100	Pearson's r	0.031	-0.172	-0.166	0.258	0.149	0.264	0.321*	0.462**	0.259	-0.086	-0.076	-0.388**	0.222	0.340*	0.362*	0.412**	0.500***
	p-value	0.841	0.259	0.276	0.087	0.327	0.080	0.032	0.001	0.086	0.572	0.622	0.008	0.142	0.022	0.014	0.005	< .001
37. 100-1k	Pearson's r	0.095	0.115	-0.086	-0.037	-0.092	-0.041	-0.065	-0.273	-0.192	0.214	-0.138	-0.347*	-0.166	-0.011	-0.048	0.362*	-0.309*
	p-value	0.536	0.451	0.576	0.808	0.547	0.787	0.673	0.070	0.206	0.157	0.368	0.019	0.276	0.942	0.752	0.014	0.039
38. 1k-10k	Pearson's r	-0.059	0.154	-0.080	0.320*	0.489***	0.061	0.127	0.027	0.222	0.361*	0.301*	-0.396**	-0.089	-0.019	-0.060	0.411**	-0.243
	p-value	0.700	0.312	0.601	0.032	< .001	0.689	0.406	0.862	0.144	0.015	0.045	0.007	0.563	0.902	0.694	0.005	0.108
39. 10k-100k	Pearson's r	0.066	0.138	0.050	0.085	0.362*	-0.072	-0.009	-0.082	-0.006	0.198	0.194	-0.512***	-0.200	-0.107	-0.120	0.497***	-0.329*
	p-value	0.665	0.365	0.746	0.580	0.015	0.641	0.955	0.591	0.969	0.191	0.203	< .001	0.187	0.482	0.431	< .001	0.028
40. 100k+	Pearson's r	0.042	-0.079	-0.101	-0.315*	0.285	-0.116	-0.138	-0.232	-0.073	0.145	-0.016	-0.043	0.046	-0.087	-0.045	0.035	-0.397**
	p-value	0.784	0.608	0.509	0.035	0.058	0.448	0.366	0.125	0.631	0.341	0.915	0.778	0.766	0.570	0.770	0.821	0.007
41. Swear words	Pearson's r	0.009	0.167	0.042	-0.094	-0.095	-0.109	-0.231	-0.013	-0.219	-0.100	0.189	-0.058	-0.137	-0.099	-0.115	0.041	-0.250
	p-value	0.954	0.272	0.786	0.539	0.536	0.474	0.128	0.934	0.149	0.512	0.213	0.704	0.369	0.519	0.450	0.790	0.098
42. Sexually explicit words	Pearson's r	-0.085	0.213	-0.178	0.187	-0.129	0.117	-0.211	3.722×10^{-21}	-0.093	0.038	0.288	-0.011	-0.207	-0.124	-0.127	0.041	-0.085
	p-value	0.580	0.159	0.241	0.218	0.399	0.444	0.164	1.000	0.545	0.802	0.055	0.943	0.173	0.416	0.408	0.792	0.579
43. Emojis	Pearson's r	-0.076	-0.188	0.190	0.375*	0.281	-0.048	-0.051	0.291	0.076	-0.070	0.262	-0.260	-0.105	0.060	0.034	0.232	0.166
	p-value	0.620	0.217	0.212	0.011	0.061	0.753	0.740	0.052	0.620	0.646	0.082	0.084	0.493	0.696	0.823	0.125	0.275
44. Initialisms	Pearson's r	-0.206	0.049	0.020	0.009	-0.313*	0.023	-0.235	-0.131	-0.240	-0.088	0.113	0.072	0.023	-0.067	-0.054	-0.069	-0.047
	p-value	0.174	0.749	0.897	0.954	0.036	0.881	0.121	0.393	0.113	0.566	0.459	0.636	0.883	0.662	0.726	0.654	0.757
45. Exaggerated spellings (seemingly purposeful)	Pearson's r	0.031	0.304*	-0.202	-0.116	-0.025	0.147	-0.170	-0.124	-0.074	-0.084	0.299*	0.045	-0.044	-0.023	-0.004	-0.021	-0.194
	p-value	0.840	0.042	0.183	0.447	0.869	0.335	0.264	0.418	0.628	0.583	0.046	0.769	0.776	0.882	0.980	0.893	0.202
46. Misspellings (seemingly accidental)	Pearson's r	-0.107	-0.056	0.144	-0.088	-0.125	0.053	0.052	-0.123	-0.121	-0.071	0.139	0.225	0.071	0.377*	0.332*	-0.243	0.127
	p-value	0.486	0.714	0.344	0.564	0.414	0.729	0.734	0.421	0.430	0.643	0.361	0.138	0.642	0.011	0.026	0.107	0.408
47. Smiling	Pearson's r	0.139	0.239	0.154	0.164	0.201	0.167	0.550***	0.377*	0.411**	0.109	-0.079	-0.306*	-0.093	-0.087	-0.115	0.283	0.276
	p-value	0.363	0.114	0.313	0.282	0.185	0.272	< .001	0.011	0.005	0.475	0.608	0.041	0.545	0.570	0.452	0.060	0.066
48. Positive facial expression	Pearson's r	0.164	0.248	0.079	0.173	0.190	0.207	0.565***	0.365*	0.445**	0.100	-0.107	-0.342*	-0.099	-0.046	-0.081	0.329*	0.275
	p-value	0.282	0.100	0.608	0.255	0.211	0.173	< .001	0.014	0.002	0.515	0.485	0.022	0.519	0.763	0.597	0.027	0.068
49. Neutral facial expression	Pearson's r	-0.207	-0.299*	-0.087	0.006	-0.213	0.027	-0.358*	-0.176	-0.232	-0.185	-0.131	0.119	0.110	0.156	0.186	-0.108	-0.067
	p-value	0.173	0.046	0.571	0.969	0.160	0.861	0.016	0.249	0.125	0.225	0.392	0.436	0.473	0.305	0.221	0.479	0.660

Pearson's Correlations

Variable		Birthday	Media Total	Pinned tweet	Number of images in feed	Number of videos	Self-images/selfies	Images of self with others	Images of only others (seemingly friends/acquaintances)	Diverse others	Images of only others (celebrities/memes)	Number of images without people	Original tweets in screenshot	Replies to original tweets (total)	Retweets on original tweets (total)	Likes on original tweets (total)	Retweets in screenshot	Under 10
50. Negative facial expression	Pearson's r	-0.259	-0.042	-0.016	0.031	-0.312*	-0.080	-0.271	-0.155	-0.247	-0.101	-0.055	0.120	0.141	0.091	0.144	-0.109	-0.080
	p-value	0.086	0.784	0.918	0.841	0.037	0.603	0.072	0.309	0.102	0.508	0.722	0.432	0.355	0.551	0.345	0.476	0.600
51. Dominant facial expression/pose	Pearson's r	-0.063	-0.176	-0.011	0.283	-0.016	0.044	-0.062	0.131	0.039	0.044	-0.154	0.037	0.066	0.009	0.026	-0.027	0.308*
	p-value	0.681	0.246	0.941	0.059	0.915	0.774	0.687	0.390	0.797	0.772	0.311	0.807	0.665	0.952	0.863	0.858	0.039
52. Stylish	Pearson's r	-0.052	0.008	0.081	0.327*	0.194	0.172	0.372*	0.162	0.223	0.290	-0.298*	-0.379*	-0.071	0.091	0.049	0.369*	0.073
	p-value	0.732	0.960	0.596	0.028	0.201	0.258	0.012	0.289	0.142	0.054	0.047	0.010	0.643	0.553	0.747	0.013	0.635
53. Attractive	Pearson's r	-0.004	0.022	0.074	0.404**	0.161	0.287	0.461**	0.153	0.253	0.258	-0.215	-0.442**	-0.032	0.133	0.108	0.431**	0.199
	p-value	0.978	0.888	0.630	0.006	0.292	0.056	0.001	0.316	0.094	0.087	0.156	0.002	0.834	0.382	0.480	0.003	0.190
54. Neat	Pearson's r	0.002	-0.054	0.081	0.249	0.212	0.185	0.368*	0.159	0.333*	0.236	-0.356*	-0.386**	-0.128	0.077	0.047	0.372*	0.170
	p-value	0.991	0.727	0.596	0.099	0.162	0.224	0.013	0.295	0.025	0.119	0.017	0.009	0.404	0.615	0.759	0.012	0.264
55. Posed	Pearson's r	-0.160	0.039	-0.042	0.321*	0.038	0.323*	0.225	0.234	0.090	0.251	-0.363*	-0.108	0.003	0.123	0.082	0.109	0.091
	p-value	0.292	0.797	0.783	0.031	0.807	0.031	0.137	0.122	0.559	0.096	0.014	0.481	0.985	0.420	0.592	0.477	0.552
56. Candid	Pearson's r	0.112	-0.112	-0.124	0.290	0.253	0.117	0.255	0.372*	0.435**	0.005	0.010	-0.330*	-0.026	-0.053	-0.052	0.354*	0.482***
	p-value	0.463	0.463	0.416	0.053	0.093	0.443	0.090	0.012	0.003	0.974	0.946	0.027	0.866	0.731	0.736	0.017	< .001
57. General positivity	Pearson's r	0.298*	0.117	-0.041	0.315*	0.502***	0.070	0.512***	0.529***	0.573***	0.140	-0.143	-0.493***	0.065	-0.039	-0.070	0.498***	0.447**
	p-value	0.047	0.446	0.788	0.035	< .001	0.648	< .001	< .001	< .001	0.359	0.350	< .001	0.670	0.798	0.649	< .001	0.002
58. Optimism	Pearson's r	0.309*	0.131	-0.089	0.360*	0.396**	0.051	0.303*	0.428**	0.457**	0.139	-0.169	-0.313*	-0.070	-0.166	-0.197	0.332*	0.367*
	p-value	0.039	0.389	0.559	0.015	0.007	0.741	0.043	0.003	0.002	0.361	0.266	0.037	0.645	0.276	0.195	0.026	0.013
59. Achievement	Pearson's r	0.232	0.172	-0.005	0.453**	0.446**	-0.053	0.363*	0.534***	0.630***	0.202	-0.072	-0.317*	0.083	-0.083	-0.105	0.324*	0.537***
	p-value	0.124	0.259	0.973	0.002	0.002	0.731	0.014	< .001	< .001	0.182	0.640	0.034	0.590	0.588	0.492	0.030	< .001
60. Gratitude	Pearson's r	0.178	-0.009	-0.155	0.278	0.303*	0.037	0.302*	0.501***	0.477***	0.029	-0.172	-0.245	0.053	0.004	-0.028	0.275	0.572***
	p-value	0.243	0.952	0.310	0.065	0.043	0.809	0.044	< .001	< .001	0.850	0.259	0.104	0.729	0.978	0.854	0.068	< .001
61. General negativity	Pearson's r	-0.172	-0.078	0.150	-0.339*	-0.546***	-0.128	-0.352*	-0.352*	-0.368*	-0.263	-0.021	0.421**	0.014	0.085	0.132	-0.441**	-0.384**
	p-value	0.258	0.609	0.326	0.023	< .001	0.401	0.018	0.018	0.013	0.080	0.891	0.004	0.926	0.577	0.387	0.002	0.009
62. Stress/Anxiety	Pearson's r	-0.001	-0.126	0.285	-0.190	-0.262	-0.189	-0.156	-0.207	-0.152	-0.175	0.037	0.136	-0.084	-0.056	-0.056	-0.174	-0.167
	p-value	0.992	0.409	0.057	0.211	0.083	0.213	0.305	0.173	0.318	0.250	0.811	0.374	0.581	0.716	0.714	0.252	0.272
63. Sadness	Pearson's r	-0.037	0.025	-0.059	-0.307*	-0.410**	-0.134	-0.181	-0.195	-0.190	-0.200	-0.045	0.159	0.126	0.077	0.167	-0.144	-0.345*
	p-value	0.808	0.868	0.700	0.040	0.005	0.380	0.235	0.200	0.210	0.187	0.769	0.297	0.411	0.617	0.272	0.347	0.020
64. Anger	Pearson's r	-0.020	0.005	0.036	-0.284	-0.382**	-0.271	-0.335*	-0.217	-0.301*	-0.196	-0.013	0.347*	0.015	-0.027	-0.019	-0.356*	-0.278
	p-value	0.897	0.972	0.814	0.059	0.010	0.072	0.025	0.153	0.045	0.197	0.931	0.019	0.922	0.860	0.900	0.016	0.064
65. General amount of humor	Pearson's r	-0.114	-0.104	-0.049	-0.120	-0.020	0.024	-0.067	-0.347*	-0.102	-0.081	0.344*	0.006	0.010	-0.034	0.033	-7.837×10^{-4}	-0.084
	p-value	0.455	0.496	0.750	0.434	0.898	0.876	0.660	0.019	0.506	0.597	0.021	0.969	0.949	0.824	0.831	0.996	0.584
66. Memes	Pearson's r	0.119	-0.094	0.067	0.119	0.048	-0.245	-0.260	-0.174	-0.205	0.061	0.552***	0.094	-0.092	-0.176	-0.153	-0.100	-0.162
	p-value	0.437	0.541	0.663	0.437	0.754	0.104	0.084	0.252	0.176	0.693	< .001	0.538	0.546	0.247	0.315	0.512	0.287
67. Sarcasm	Pearson's r	-0.176	-0.136	-0.054	-0.175	-0.220	0.018	-0.240	-0.320*	-0.162	-0.119	0.064	0.284	-0.054	-0.049	0.001	-0.275	-0.090
	p-value	0.247	0.374	0.723	0.250	0.146	0.908	0.112	0.032	0.287	0.435	0.675	0.058	0.725	0.748	0.993	0.067	0.558

Pearson's Correlations

Variable		Birthday	Media Total	Pinned tweet	Number of images in feed	Number of videos	Self-images/selfies	Images of self with others	Images of only others (seemingly friends/acquaintances)	Diverse others	Images of only others (celebrities/memes)	Number of images without people	Original tweets in screenshot	Replies to original tweets (total)	Retweets on original tweets (total)	Likes on original tweets (total)	Retweets in screenshot	Under 10
68. Mentions of Specific Others Unknown	Pearson's r	0.184	-0.092	0.153	0.101	-0.015	-0.217	-0.178	-0.265	-0.233	0.387**	-0.206	0.039	-0.256	-0.100	-0.149	-0.056	-0.386**
	p-value	0.227	0.547	0.316	0.508	0.924	0.152	0.243	0.078	0.124	0.009	0.174	0.801	0.089	0.512	0.330	0.717	0.009
69. Mentions of Specific Others Known	Pearson's r	0.192	-0.109	-0.089	-8.548×10^{-4}	-0.009	0.010	0.083	0.475***	0.101	-0.331*	-0.183	0.021	0.258	0.235	0.248	-0.014	0.498***
	p-value	0.207	0.478	0.559	0.996	0.955	0.947	0.586	< .001	0.509	0.027	0.228	0.891	0.087	0.120	0.100	0.929	< .001
70. Mentions of Generic Others	Pearson's r	0.104	0.240	0.010	-0.026	-0.179	-0.258	-0.127	-0.085	0.015	-0.039	0.048	0.086	-0.180	-0.227	-0.231	-0.087	-0.116
	p-value	0.498	0.113	0.946	0.864	0.239	0.087	0.406	0.579	0.922	0.800	0.753	0.574	0.236	0.134	0.128	0.569	0.447
71. Pertaining to non-romantic relationships	Pearson's r	0.307*	0.126	0.027	0.131	0.123	-0.192	0.229	-0.098	0.048	0.212	0.048	-0.058	0.091	-0.061	-0.064	0.057	0.017
	p-value	0.040	0.408	0.860	0.391	0.421	0.205	0.131	0.523	0.756	0.161	0.753	0.705	0.554	0.690	0.674	0.712	0.914
72. Pertaining to romantic relationships	Pearson's r	-0.021	-0.066	-0.430**	-0.288	-0.109	0.070	-0.062	-0.095	-0.100	-0.201	-0.350*	0.010	0.065	0.127	0.145	0.056	0.094
	p-value	0.893	0.667	0.003	0.055	0.476	0.648	0.684	0.533	0.515	0.185	0.018	0.950	0.674	0.406	0.342	0.714	0.540
73. Sexual content	Pearson's r	-0.027	0.012	-0.189	0.133	-0.195	-0.010	-0.232	-0.141	-0.246	0.111	0.170	0.056	-0.110	-0.061	-0.024	-0.025	-0.159
	p-value	0.862	0.940	0.214	0.385	0.198	0.947	0.125	0.355	0.103	0.467	0.264	0.716	0.470	0.689	0.875	0.870	0.297
74. Pertaining to Academics	Pearson's r	0.099	0.071	0.254	-0.092	-0.096	-0.142	0.207	0.148	0.164	-0.244	0.055	-0.075	0.064	-0.043	-0.043	0.039	0.199
	p-value	0.519	0.645	0.092	0.549	0.530	0.352	0.172	0.333	0.280	0.106	0.722	0.625	0.677	0.781	0.780	0.797	0.190
75. Pertaining to Work	Pearson's r	0.077	0.232	-0.184	0.031	-0.257	-0.056	-0.073	-0.034	-0.025	-0.050	0.131	-0.204	0.133	0.260	0.251	0.230	0.211
	p-value	0.617	0.125	0.226	0.842	0.089	0.713	0.633	0.826	0.872	0.746	0.393	0.178	0.385	0.084	0.096	0.129	0.165
76. Pertaining to Movies/TV	Pearson's r	-0.111	-0.113	0.056	0.051	0.039	-0.181	-0.269	-0.274	-0.271	0.251	0.202	0.115	0.022	0.120	0.101	-0.121	-0.033
	p-value	0.469	0.461	0.715	0.737	0.801	0.233	0.074	0.068	0.071	0.096	0.182	0.452	0.885	0.432	0.510	0.428	0.827
77. Pertaining to Music	Pearson's r	0.023	-0.063	0.130	0.010	0.060	-0.054	-0.065	-0.238	-0.185	0.154	0.064	-0.165	-0.275	-0.055	-0.074	0.151	-0.228
	p-value	0.883	0.683	0.395	0.949	0.695	0.727	0.673	0.116	0.224	0.312	0.674	0.278	0.068	0.718	0.630	0.321	0.132
78. Pertaining to Art	Pearson's r	0.201	-0.005	-0.102	0.063	-0.065	-0.263	-0.201	-0.170	-0.177	-0.024	0.453**	0.012	0.170	-0.032	0.037	0.007	-0.051
	p-value	0.185	0.973	0.504	0.683	0.673	0.081	0.185	0.263	0.244	0.875	0.002	0.938	0.263	0.836	0.808	0.966	0.738
79. Pertaining to Sports	Pearson's r	-0.034	-0.029	-0.071	0.374*	0.510***	0.112	0.377*	0.446**	0.528***	0.311*	-0.161	-0.348*	-0.003	-0.036	-0.037	0.363*	0.316*
	p-value	0.826	0.849	0.643	0.011	< .001	0.465	0.011	0.002	< .001	0.037	0.291	0.019	0.983	0.814	0.810	0.014	0.034
80. Pertaining to Other Hobbies/Interests	Pearson's r	0.128	0.288	0.011	0.007	-0.194	-0.233	-0.086	0.026	-0.007	-0.170	0.254	0.074	0.243	-0.085	-0.073	-0.073	0.155
	p-value	0.401	0.055	0.944	0.963	0.202	0.124	0.576	0.866	0.962	0.265	0.092	0.628	0.107	0.578	0.634	0.635	0.309
81. Political content	Pearson's r	-0.009	0.077	0.046	-0.073	-0.256	-0.196	-0.319*	-0.173	-0.215	-0.019	0.208	0.249	-0.149	-0.120	-0.128	-0.252	-0.184
	p-value	0.956	0.614	0.763	0.635	0.089	0.198	0.033	0.255	0.157	0.903	0.171	0.099	0.330	0.433	0.401	0.095	0.226
82. Religious content	Pearson's r	0.095	-0.067	-0.121	6.370×10^{-4}	0.156	-0.038	0.137	0.039	0.330*	-0.031	0.167	-0.099	0.134	-0.026	0.017	0.119	0.184
	p-value	0.534	0.660	0.430	0.997	0.307	0.803	0.371	0.801	0.027	0.838	0.272	0.516	0.379	0.866	0.910	0.434	0.227

* p < .05, ** p < .01, *** p < .001

Pearson's Correlations

Variable		10-100	100-1k	1k-10k	10k-100k	100k+	Swear words	Sexually explicit words	Emojis	Initialisms	Exaggerated spellings (seemingly purposeful)	Misspellings (seemingly accidental)	Smiling	Positive facial expression	Neutral facial expression	Negative facial expression	Dominant facial expression/pose	Stylish
36. 10-100	Pearson's r	—																
	p-value	—																
37. 100-1k	Pearson's r	-0.057	—															
	p-value	0.708	—															
38. 1k-10k	Pearson's r	-0.170	0.125	—														
	p-value	0.266	0.414	—														
39. 10k-100k	Pearson's r	-0.153	-0.100	0.167	—													
	p-value	0.317	0.515	0.272	—													
40. 100k+	Pearson's r	-0.168	-0.160	-0.005	0.343*	—												
	p-value	0.269	0.295	0.976	0.021	—												
41. Swear words	Pearson's r	-0.251	-0.099	0.134	0.363*	0.214	—											
	p-value	0.097	0.516	0.381	0.014	0.158	—											
42. Sexually explicit words	Pearson's r	-0.042	-0.173	0.285	0.160	-0.104	0.299*	—										
	p-value	0.786	0.254	0.058	0.294	0.495	0.046	—										
43. Emojis	Pearson's r	0.147	-0.236	0.244	0.184	-0.055	0.126	0.288	—									
	p-value	0.336	0.118	0.106	0.227	0.719	0.409	0.055	—									
44. Initialisms	Pearson's r	-0.230	0.094	0.080	-0.060	-0.101	0.332*	0.192	0.125	—								
	p-value	0.129	0.539	0.600	0.696	0.510	0.026	0.206	0.415	—								
45. Exaggerated spellings (seemingly purposeful)	Pearson's r	-0.169	-0.205	0.156	0.304*	0.074	0.358*	0.415**	0.101	0.097	—							
	p-value	0.266	0.177	0.307	0.043	0.631	0.016	0.005	0.509	0.525	—							
46. Misspellings (seemingly accidental)	Pearson's r	-0.052	-0.129	-0.243	-0.107	-0.131	-0.222	-0.099	-0.093	-0.132	-0.127	—						
	p-value	0.733	0.400	0.108	0.484	0.390	0.143	0.516	0.544	0.389	0.407	—						
47. Smiling	Pearson's r	0.316*	-0.012	0.031	0.055	-0.180	-0.041	-0.062	-0.159	-0.265	-0.072	-0.120	—					
	p-value	0.035	0.936	0.838	0.719	0.237	0.788	0.686	0.297	0.079	0.640	0.434	—					
48. Positive facial expression	Pearson's r	0.299*	0.039	0.119	0.026	-0.175	-0.077	0.012	-0.180	-0.305*	-0.019	-0.109	0.944***	—				
	p-value	0.046	0.801	0.435	0.864	0.250	0.614	0.939	0.236	0.042	0.902	0.478	< .001	—				
49. Neutral facial expression	Pearson's r	3.625×10^{-4}	0.035	-0.184	-0.068	0.045	0.077	-0.030	0.190	0.331*	0.096	-0.118	-0.681***	-0.614***	—			
	p-value	0.997	0.821	0.227	0.655	0.771	0.614	0.844	0.212	0.026	0.530	0.442	< .001	< .001	—			
50. Negative facial expression	Pearson's r	-0.063	0.120	-0.087	-0.133	-0.064	0.229	0.038	0.020	0.480***	0.015	-0.181	-0.365*	-0.351*	0.597***	—		
	p-value	0.682	0.431	0.570	0.385	0.678	0.130	0.804	0.896	< .001	0.924	0.234	0.014	0.018	< .001	—		
51. Dominant facial expression/pose	Pearson's r	0.311*	-0.141	-0.226	-0.169	-0.208	-0.016	-0.099	0.154	0.264	0.086	-0.189	-0.231	-0.277	0.648***	0.443**	—	
	p-value	0.037	0.357	0.136	0.266	0.171	0.919	0.518	0.311	0.079	0.576	0.213	0.126	0.066	< .001	0.002	—	
52. Stylish	Pearson's r	0.111	0.180	0.189	0.160	-0.129	-0.162	-0.034	-0.020	-0.075	-0.027	-0.214	0.465**	0.612***	-0.078	0.029	-0.008	—
	p-value	0.467	0.236	0.214	0.295	0.400	0.287	0.822	0.898	0.626	0.860	0.159	0.001	< .001	0.612	0.848	0.957	—
53. Attractive	Pearson's r	0.195	0.061	0.172	0.222	-0.144	-0.005	0.213	0.152	0.134	0.017	-0.088	0.465**	0.581***	-0.094	0.085	0.034	0.782***
	p-value	0.200	0.692	0.258	0.143	0.347	0.972	0.159	0.318	0.380	0.913	0.566	0.001	< .001	0.538	0.578	0.822	< .001
54. Neat	Pearson's r	0.175	0.059	0.110	0.163	-0.054	-0.119	-0.014	-0.082	-0.178	0.088	-0.074	0.531***	0.628***	-0.063	-0.088	0.065	0.766***
	p-value	0.249	0.701	0.472	0.285	0.723	0.436	0.925	0.590	0.242	0.565	0.628	< .001	< .001	0.682	0.565	0.673	< .001

Pearson's Correlations

Variable		10-100	100-1k	1k-10k	10k-100k	100k+	Swear words	Sexually explicit words	Emojis	Initialisms	Exaggerated spellings (seemingly purposeful)	Misspellings (seemingly accidental)	Smiling	Positive facial expression	Neutral facial expression	Negative facial expression	Dominant facial expression/pose	Stylish
55. Posed	Pearson's r	0.208	-0.002	-0.098	0.019	-0.098	0.074	0.040	-0.054	0.087	0.021	-0.178	0.499***	0.528***	0.105	0.135	0.247	0.622***
	p-value	0.171	0.992	0.522	0.904	0.523	0.627	0.793	0.727	0.569	0.894	0.243	< .001	< .001	0.491	0.375	0.101	< .001
56. Candid	Pearson's r	0.450**	0.138	0.198	-0.298*	-0.286	-0.113	-0.116	-0.008	0.071	-0.011	-0.268	0.223	0.271	0.068	0.015	0.462**	0.213
	p-value	0.002	0.366	0.193	0.047	0.057	0.460	0.446	0.960	0.645	0.942	0.076	0.140	0.071	0.659	0.922	0.001	0.161
57. General positivity	Pearson's r	0.399**	0.023	0.258	-0.007	-0.088	-0.267	-0.103	0.096	-0.254	-0.100	-0.096	0.582***	0.604***	-0.443**	-0.411**	-0.022	0.463**
	p-value	0.007	0.881	0.087	0.962	0.565	0.076	0.502	0.529	0.093	0.513	0.529	< .001	< .001	0.002	0.005	0.885	0.001
58. Optimism	Pearson's r	0.222	0.080	0.276	-0.132	-0.242	-0.236	-0.057	0.203	-0.131	0.060	-0.161	0.372*	0.410**	-0.201	-0.197	0.246	0.401**
	p-value	0.143	0.600	0.066	0.389	0.110	0.119	0.711	0.180	0.393	0.698	0.291	0.012	0.005	0.187	0.195	0.104	0.006
59. Achievement	Pearson's r	0.380**	-0.089	0.126	-0.143	-0.195	-0.302*	-0.221	0.100	-0.312*	-0.082	-0.165	0.458**	0.431**	-0.276	-0.215	0.263	0.253
	p-value	0.010	0.562	0.408	0.350	0.200	0.044	0.144	0.515	0.037	0.591	0.278	0.002	0.003	0.067	0.156	0.081	0.094
60. Gratitude	Pearson's r	0.457**	-0.022	0.139	-0.322*	-0.298*	-0.289	-0.160	0.009	-0.148	-0.086	-0.067	0.292	0.311*	-0.158	-0.214	0.327*	0.241
	p-value	0.002	0.884	0.363	0.031	0.047	0.054	0.294	0.951	0.333	0.573	0.662	0.052	0.038	0.301	0.159	0.028	0.111
61. General negativity	Pearson's r	-0.259	0.015	-0.266	-0.094	0.151	0.224	-0.034	-0.194	0.219	-0.023	-0.037	-0.389**	-0.369*	0.380*	0.453**	-0.052	-0.203
	p-value	0.086	0.923	0.078	0.540	0.321	0.140	0.823	0.201	0.148	0.881	0.807	0.008	0.012	0.010	0.002	0.736	0.182
62. Stress/Anxiety	Pearson's r	-0.275	-0.135	-0.156	0.191	0.160	0.264	-0.251	-0.073	0.168	0.241	-0.110	-0.253	-0.262	0.268	0.260	0.081	-0.061
	p-value	0.067	0.376	0.306	0.209	0.292	0.079	0.096	0.633	0.270	0.111	0.472	0.093	0.082	0.075	0.084	0.595	0.692
63. Sadness	Pearson's r	-0.165	0.068	-0.032	0.070	0.215	0.145	-0.019	-0.197	0.099	0.136	-0.184	-0.302*	-0.297*	0.174	0.270	-0.034	-0.166
	p-value	0.279	0.658	0.834	0.647	0.156	0.342	0.901	0.195	0.518	0.374	0.227	0.044	0.047	0.253	0.073	0.827	0.277
64. Anger	Pearson's r	-0.281	0.039	-0.169	-0.118	0.086	0.257	-0.050	-0.253	0.124	-0.112	-0.009	-0.447**	-0.420**	0.395**	0.462**	0.050	-0.330*
	p-value	0.061	0.797	0.268	0.441	0.575	0.089	0.747	0.094	0.416	0.465	0.951	0.002	0.004	0.007	0.001	0.743	0.027
65. General amount of humor	Pearson's r	-0.058	-0.385**	0.121	0.324*	0.270	0.196	0.392**	0.031	0.027	0.259	0.124	-0.233	-0.163	-0.002	0.008	-0.176	-0.131
	p-value	0.704	0.009	0.428	0.030	0.073	0.197	0.008	0.839	0.859	0.086	0.417	0.124	0.286	0.991	0.960	0.246	0.393
66. Memes	Pearson's r	-0.237	-0.182	0.163	0.172	0.118	0.250	0.126	0.110	0.129	0.278	0.069	-0.288	-0.315*	-0.050	0.025	-0.030	-0.404**
	p-value	0.117	0.232	0.283	0.257	0.441	0.098	0.408	0.471	0.398	0.064	0.654	0.055	0.035	0.744	0.872	0.844	0.006
67. Sarcasm	Pearson's r	-0.218	-0.295*	-0.151	0.079	0.220	0.157	0.137	-0.191	0.023	0.217	0.076	-0.396**	-0.300*	0.349*	0.401**	0.183	-0.174
	p-value	0.150	0.049	0.323	0.607	0.147	0.302	0.371	0.209	0.883	0.153	0.619	0.007	0.046	0.019	0.006	0.228	0.254
68. Mentions of Specifc Others Unknown	Pearson's r	-0.162	0.448**	-0.014	-0.088	0.088	-0.202	-0.261	-0.266	-0.221	-0.314*	0.164	-0.211	-0.200	0.089	-0.076	-0.034	-0.107
	p-value	0.287	0.002	0.929	0.564	0.567	0.183	0.084	0.078	0.144	0.036	0.282	0.165	0.187	0.562	0.618	0.823	0.485
69. Mentions of Specific Others Known	Pearson's r	0.314*	-0.311*	-0.165	-0.206	-0.088	-0.041	-0.131	0.205	0.010	0.013	0.174	-0.016	-0.050	-0.067	-0.064	0.086	-0.150
	p-value	0.036	0.038	0.279	0.176	0.567	0.788	0.392	0.176	0.949	0.935	0.253	0.919	0.744	0.661	0.675	0.575	0.326
70. Mentions of Generic Others	Pearson's r	-0.136	-0.135	0.064	0.082	0.039	0.133	0.261	-0.095	-0.026	0.006	0.013	-0.068	-0.022	-0.057	0.094	-0.064	-0.106
	p-value	0.372	0.376	0.678	0.592	0.799	0.385	0.083	0.536	0.864	0.970	0.930	0.655	0.885	0.708	0.541	0.675	0.487
71. Pertaining to non-romantic relationships	Pearson's r	0.110	-0.220	0.181	0.074	0.073	-0.055	0.109	-0.046	-0.097	0.111	-0.004	-0.003	0.050	-0.100	0.033	0.142	0.107
	p-value	0.470	0.146	0.235	0.628	0.635	0.722	0.475	0.767	0.526	0.469	0.977	0.983	0.746	0.515	0.829	0.351	0.484
72. Pertaining to romantic relationships	Pearson's r	0.099	0.212	-0.097	-0.136	-0.185	0.027	0.145	0.013	0.077	-0.038	-0.119	-0.087	-0.007	0.133	0.174	0.020	0.118
	p-value	0.516	0.161	0.525	0.374	0.224	0.861	0.342	0.930	0.615	0.803	0.436	0.568	0.961	0.384	0.253	0.896	0.440

Pearson's Correlations

Variable		10-100	100-1k	1k-10k	10k-100k	100k+	Swear words	Sexually explicit words	Emojis	Initialisms	Exaggerated spellings (seemingly purposeful)	Misspellings (seemingly accidental)	Smiling	Positive facial expression	Neutral facial expression	Negative facial expression	Dominant facial expression/pose	Stylish
73. Sexual content	Pearson's r	-0.058	0.089	0.328*	-0.115	-0.166	0.103	0.646***	0.230	0.252	0.078	-0.096	-0.274	-0.213	-0.003	-0.022	-0.151	-0.229
	p-value	0.703	0.562	0.028	0.450	0.277	0.502	< .001	0.129	0.095	0.610	0.529	0.069	0.161	0.982	0.885	0.323	0.131
74. Pertaining to Academics	Pearson's r	0.233	-0.256	-0.166	0.104	0.006	0.232	-0.053	0.092	-0.158	0.232	-0.219	0.190	0.121	-0.050	-0.010	0.142	0.004
	p-value	0.123	0.089	0.276	0.497	0.968	0.125	0.728	0.547	0.299	0.124	0.148	0.211	0.427	0.743	0.949	0.351	0.978
75. Pertaining to Work	Pearson's r	0.215	0.045	-0.077	0.044	-0.063	0.152	0.127	-0.069	0.026	0.163	0.020	0.030	0.123	0.120	0.017	0.041	0.136
	p-value	0.156	0.770	0.613	0.772	0.682	0.320	0.406	0.653	0.864	0.284	0.896	0.847	0.420	0.433	0.910	0.790	0.374
76. Pertaining to Movies/TV	Pearson's r	-0.148	-0.188	-0.136	0.153	0.189	-0.194	0.052	0.122	-0.089	-0.116	0.473**	-0.291	-0.318*	-0.059	-0.197	-0.182	-0.232
	p-value	0.331	0.215	0.374	0.317	0.213	0.202	0.734	0.425	0.563	0.448	0.001	0.052	0.033	0.702	0.194	0.232	0.124
77. Pertaining to Music	Pearson's r	-0.203	0.411**	0.239	0.036	-0.063	-0.034	0.111	0.166	0.057	-0.175	0.064	-0.122	-0.059	-0.042	0.023	-0.264	0.048
	p-value	0.180	0.005	0.115	0.813	0.682	0.823	0.467	0.277	0.708	0.249	0.675	0.426	0.702	0.782	0.883	0.080	0.756
78. Pertaining to Art	Pearson's r	-0.059	0.011	0.151	0.006	-0.054	-0.060	0.070	0.230	0.035	-0.094	0.059	-0.284	-0.332*	-0.162	-0.074	-0.173	-0.454**
	p-value	0.702	0.943	0.321	0.969	0.723	0.697	0.646	0.128	0.821	0.539	0.700	0.059	0.026	0.289	0.629	0.257	0.002
79. Pertaining to Sports	Pearson's r	0.379*	-0.027	0.314*	-0.074	-0.111	-0.224	-0.112	0.058	-0.157	-0.080	-0.211	0.357*	0.333*	-0.146	-0.217	0.348*	0.316*
	p-value	0.010	0.860	0.036	0.627	0.469	0.139	0.465	0.706	0.305	0.601	0.164	0.016	0.026	0.340	0.153	0.019	0.034
80. Pertaining to Other Hobbies/Interests	Pearson's r	-0.242	-0.069	0.073	-0.044	-0.249	0.104	0.005	-0.062	0.190	0.016	-0.085	0.051	0.043	0.007	0.036	0.007	0.030
	p-value	0.110	0.655	0.634	0.777	0.099	0.498	0.974	0.685	0.211	0.915	0.581	0.737	0.778	0.964	0.814	0.966	0.844
81. Political content	Pearson's r	-0.118	0.004	-0.220	-0.029	0.021	-0.167	-0.080	-0.272	-0.188	-0.130	0.189	-0.211	-0.209	-0.028	0.005	-0.115	-0.296*
	p-value	0.442	0.980	0.147	0.851	0.891	0.273	0.603	0.071	0.216	0.395	0.215	0.165	0.167	0.857	0.973	0.453	0.049
82. Religious content	Pearson's r	0.084	-0.106	0.080	-0.014	0.132	-0.198	0.069	-0.043	-0.013	-0.106	-0.105	-0.021	-0.064	-0.213	0.081	-0.119	-0.136
	p-value	0.586	0.490	0.599	0.927	0.389	0.193	0.654	0.778	0.931	0.489	0.494	0.891	0.678	0.161	0.598	0.435	0.372

* p < .05, ** p < .01, *** p < .001

Pearson's Correlations

Variable		Attractive	Neat	Posed	Candid	General positivity	Optimism	Achievement	Gratitude	General negativity	Stress/Anxiety	Sadness	Anger	General amount of humor	Memes	Sarcasm	Mentions of Specifc Others Unknown	Mentions of Specific Others Known	Mentions of Generic Others
53. Attractive	Pearson's r	—																	
	p-value	—																	
54. Neat	Pearson's r	0.663***	—																
	p-value	< .001	—																
55. Posed	Pearson's r	0.638***	0.697***	—															
	p-value	< .001	< .001	—															
56. Candid	Pearson's r	0.182	0.220	0.097	—														
	p-value	0.233	0.146	0.527	—														
57. General positivity	Pearson's r	0.420**	0.416**	0.186	0.487***	—													
	p-value	0.004	0.004	0.221	< .001	—													
58. Optimism	Pearson's r	0.342*	0.402**	0.189	0.530***	0.816***	—												
	p-value	0.021	0.006	0.215	< .001	< .001	—												
59. Achievement	Pearson's r	0.195	0.276	0.135	0.574***	0.759***	0.746***	—											
	p-value	0.200	0.066	0.377	< .001	< .001	< .001	—											
60. Gratitude	Pearson's r	0.107	0.309*	0.062	0.718***	0.726***	0.784***	0.775***	—										
	p-value	0.484	0.039	0.687	< .001	< .001	< .001	< .001	—										
61. General negativity	Pearson's r	-0.315*	-0.202	-0.088	-0.341*	-0.777***	-0.705***	-0.579***	-0.579***	—									
	p-value	0.035	0.183	0.567	0.022	< .001	< .001	< .001	< .001	—									
62. Stress/Anxiety	Pearson's r	-0.179	-0.006	-0.093	-0.194	-0.472**	-0.367*	-0.241	-0.335*	0.647***	—								
	p-value	0.241	0.967	0.542	0.201	0.001	0.013	0.110	0.024	< .001	—								
63. Sadness	Pearson's r	-0.217	-0.175	-0.294	-0.159	-0.390**	-0.273	-0.334*	-0.297*	0.543***	0.506***	—							
	p-value	0.152	0.250	0.050	0.296	0.008	0.070	0.025	0.047	< .001	< .001	—							
64. Anger	Pearson's r	-0.451**	-0.309*	-0.142	-0.250	-0.699***	-0.622***	-0.464**	-0.433**	0.754***	0.411**	0.285	—						
	p-value	0.002	0.039	0.351	0.097	< .001	< .001	0.001	0.003	< .001	0.005	0.058	—						
65. General amount of humor	Pearson's r	0.037	-0.204	-0.303*	-0.212	-0.212	-0.320*	-0.322*	-0.296*	0.076	0.090	0.029	-0.005	—					
	p-value	0.807	0.179	0.043	0.162	0.163	0.032	0.031	0.048	0.618	0.556	0.851	0.973	—					
66. Memes	Pearson's r	-0.272	-0.435**	-0.519***	-0.050	-0.196	-0.092	-0.107	-0.113	-0.023	0.164	0.066	-0.034	0.533***	—				
	p-value	0.071	0.003	< .001	0.743	0.198	0.547	0.484	0.462	0.881	0.282	0.665	0.826	< .001	—				
67. Sarcasm	Pearson's r	-0.079	-0.144	-0.178	-0.172	-0.527***	-0.364*	-0.333*	-0.312*	0.338*	0.280	0.290	0.383**	0.563***	0.439**	—			
	p-value	0.608	0.347	0.243	0.258	< .001	0.014	0.025	0.037	0.023	0.062	0.053	0.009	< .001	0.003	—			
68. Mentions of Specifc Others Unknown	Pearson's r	-0.294	0.058	-0.093	-0.121	-0.187	-0.058	-0.092	-0.035	0.175	0.110	0.042	0.295*	-0.232	0.072	-0.041	—		
	p-value	0.050	0.703	0.544	0.429	0.218	0.703	0.546	0.818	0.251	0.471	0.783	0.049	0.126	0.639	0.789	—		

Pearson's Correlations

Variable		Attractive	Neat	Posed	Candid	General positivity	Optimism	Achievement	Gratitude	General negativity	Stress/Anxiety	Sadness	Anger	General amount of humor	Memes	Sarcasm	Mentions of Specific Others Unknown	Mentions of Specific Others Known	Mentions of Generic Others
69. Mentions of Specific Others Known	Pearson's r	-0.026	-0.107	-0.091	0.150	0.304*	0.217	0.211	0.344*	-0.266	-0.135	-0.112	-0.141	-0.172	-0.106	-0.190	-0.358*	—	
	p-value	0.867	0.485	0.551	0.326	0.043	0.153	0.164	0.021	0.077	0.376	0.463	0.355	0.259	0.489	0.211	0.016	—	
70. Mentions of Generic Others	Pearson's r	-0.140	0.045	-0.079	-0.147	-0.194	-0.090	-0.028	0.036	0.255	0.148	0.012	0.469**	0.186	0.064	0.249	0.276	-0.154	—
	p-value	0.360	0.769	0.606	0.334	0.202	0.558	0.857	0.812	0.091	0.333	0.937	0.001	0.222	0.676	0.099	0.066	0.314	—
71. Pertaining to non-romantic relationships	Pearson's r	0.126	0.085	-0.063	0.052	0.245	0.219	0.243	0.252	-0.150	0.053	-0.137	-0.010	0.345*	0.224	0.079	0.138	-0.002	0.511***
	p-value	0.411	0.578	0.681	0.734	0.104	0.149	0.108	0.096	0.326	0.730	0.370	0.949	0.020	0.140	0.605	0.366	0.989	< .001
72. Pertaining to romantic relationships	Pearson's r	0.148	0.045	0.016	0.043	-0.019	0.108	-0.170	0.139	-0.057	-0.296*	-0.035	-0.081	-0.032	-0.185	0.050	-0.191	0.131	-0.094
	p-value	0.332	0.767	0.916	0.778	0.899	0.481	0.265	0.362	0.709	0.048	0.817	0.599	0.835	0.223	0.742	0.210	0.392	0.540
73. Sexual content	Pearson's r	-0.005	-0.266	-0.195	-0.088	-0.210	-0.128	-0.282	-0.136	0.016	-0.349*	0.022	0.058	0.208	0.146	-0.014	-0.011	0.002	0.171
	p-value	0.974	0.077	0.200	0.563	0.167	0.402	0.060	0.372	0.916	0.019	0.884	0.707	0.171	0.340	0.928	0.941	0.991	0.261
74. Pertaining to Academics	Pearson's r	-0.058	-0.037	-0.007	-0.007	0.087	-0.004	0.230	0.051	0.122	0.420**	0.095	-0.042	0.167	0.017	-0.067	-0.296*	0.062	-0.042
	p-value	0.706	0.811	0.962	0.965	0.572	0.981	0.129	0.737	0.424	0.004	0.534	0.785	0.272	0.912	0.664	0.048	0.685	0.785
75. Pertaining to Work	Pearson's r	0.073	0.131	0.102	0.142	0.019	-0.027	0.103	0.150	0.081	0.057	-0.028	0.157	0.153	-0.077	0.030	-0.008	0.049	0.340*
	p-value	0.631	0.389	0.505	0.351	0.900	0.860	0.500	0.325	0.599	0.710	0.853	0.304	0.316	0.616	0.843	0.960	0.751	0.022
76. Pertaining to Movies/TV	Pearson's r	-0.106	-0.258	-0.296*	-0.459**	-0.075	-0.198	-0.147	-0.276	-0.126	-0.086	-0.151	-0.164	0.312*	0.214	0.055	0.147	-0.023	-0.113
	p-value	0.489	0.087	0.048	0.002	0.623	0.193	0.335	0.067	0.411	0.575	0.321	0.281	0.037	0.158	0.719	0.335	0.882	0.460
77. Pertaining to Music	Pearson's r	0.117	-0.147	-0.182	-0.045	-0.050	0.022	-0.230	-0.188	-0.077	-0.325*	-0.122	-0.081	0.070	0.155	-0.104	0.203	-0.249	-0.220
	p-value	0.444	0.336	0.231	0.768	0.746	0.888	0.128	0.216	0.617	0.029	0.426	0.598	0.646	0.308	0.495	0.181	0.099	0.146
78. Pertaining to Art	Pearson's r	-0.276	-0.592***	-0.644***	-0.134	-0.112	-0.025	-0.105	-0.117	-0.141	-0.130	0.189	-0.068	0.325*	0.559***	0.120	0.002	0.082	0.051
	p-value	0.067	< .001	< .001	0.380	0.462	0.869	0.494	0.444	0.354	0.393	0.214	0.655	0.030	< .001	0.432	0.991	0.592	0.739
79. Pertaining to Sports	Pearson's r	0.255	0.397**	0.238	0.669***	0.645***	0.629***	0.720***	0.698***	-0.512***	-0.305*	-0.173	-0.438**	-0.274	-0.239	-0.309*	-0.075	0.101	-0.111
	p-value	0.091	0.007	0.115	< .001	< .001	< .001	< .001	< .001	< .001	0.042	0.257	0.003	0.069	0.115	0.039	0.623	0.509	0.468
80. Pertaining to Other Hobbies/Interests	Pearson's r	-0.033	-0.103	-0.037	0.048	0.061	0.073	0.103	0.074	-0.062	-0.067	-0.074	-0.018	0.010	0.010	-0.092	-0.318*	0.063	-0.052
	p-value	0.828	0.500	0.808	0.757	0.689	0.636	0.503	0.628	0.687	0.664	0.629	0.909	0.950	0.949	0.550	0.034	0.680	0.736
81. Political content	Pearson's r	-0.483***	-0.283	-0.327*	-0.245	-0.383**	-0.346*	-0.146	-0.146	0.322*	0.182	0.083	0.508***	0.089	0.235	0.344*	0.436**	-0.196	0.648***
	p-value	< .001	0.060	0.029	0.105	0.009	0.020	0.340	0.337	0.031	0.231	0.587	< .001	0.560	0.120	0.021	0.003	0.198	< .001
82. Religious content	Pearson's r	-0.090	-0.064	-0.362*	0.198	0.118	-0.030	0.155	0.125	0.027	0.033	0.212	0.047	0.082	0.132	0.089	-0.120	0.146	0.186
	p-value	0.567	0.674	0.015	0.193	0.440	0.844	0.308	0.415	0.860	0.830	0.162	0.758	0.590	0.386	0.563	0.432	0.340	0.220

* p < .05, ** p < .01, *** p < .001

Pearson's Correlations

Variable		Pertaining to non-romantic relationships	Pertaining to romantic relationships	Sexual content	Pertaining to Academics	Pertaining to Work	Pertaining to Movies/TV	Pertaining to Music	Pertaining to Art	Pertaining to Sports	Pertaining to Other Hobbies/Interests	Political content	Religious content
71. Pertaining to non-romantic relationships	Pearson's r	—											
	p-value	—											
72. Pertaining to romantic relationships	Pearson's r	-0.149	—										
	p-value	0.327	—										
73. Sexual content	Pearson's r	0.044	0.279	—									
	p-value	0.773	0.064	—									
74. Pertaining to Academics	Pearson's r	0.250	-0.137	-0.322*	—								
	p-value	0.098	0.370	0.031	—								
75. Pertaining to Work	Pearson's r	0.217	0.011	0.128	0.094	—							
	p-value	0.153	0.945	0.401	0.540	—							
76. Pertaining to Movies/TV	Pearson's r	0.130	-0.074	0.130	-0.171	-4.551×10^{-4}	—						
	p-value	0.396	0.629	0.394	0.260	0.998	—						
77. Pertaining to Music	Pearson's r	-0.219	0.262	0.321*	-0.365*	-0.190	0.180	—					
	p-value	0.148	0.082	0.032	0.014	0.212	0.236	—					
78. Pertaining to Art	Pearson's r	0.080	0.008	0.383**	-0.172	0.033	0.340*	0.306*	—				
	p-value	0.602	0.960	0.009	0.258	0.830	0.022	0.041	—				
79. Pertaining to Sports	Pearson's r	0.125	-0.108	-0.111	0.046	-0.076	-0.298*	-0.231	-0.285	—			
	p-value	0.413	0.480	0.470	0.763	0.621	0.047	0.126	0.058	—			
80. Pertaining to Other Hobbies/Interests	Pearson's r	0.055	0.063	0.035	0.217	0.250	-0.078	-0.159	0.080	-0.016	—		
	p-value	0.719	0.679	0.821	0.152	0.097	0.611	0.297	0.602	0.918	—		
81. Political content	Pearson's r	0.175	-0.282	-7.723×10^{-4}	-0.209	0.295*	0.139	-0.174	0.252	-0.330*	-0.156	—	
	p-value	0.250	0.060	0.996	0.168	0.050	0.363	0.253	0.095	0.027	0.306	—	
82. Religious content	Pearson's r	0.136	-0.173	0.006	-0.154	-0.033	-0.028	-0.216	0.210	0.141	-0.137	0.228	—
	p-value	0.374	0.257	0.970	0.311	0.828	0.854	0.155	0.166	0.357	0.371	0.131	—

* p < .05, ** p < .01, *** p < .001

Figure B1

Instagram Scree Plot

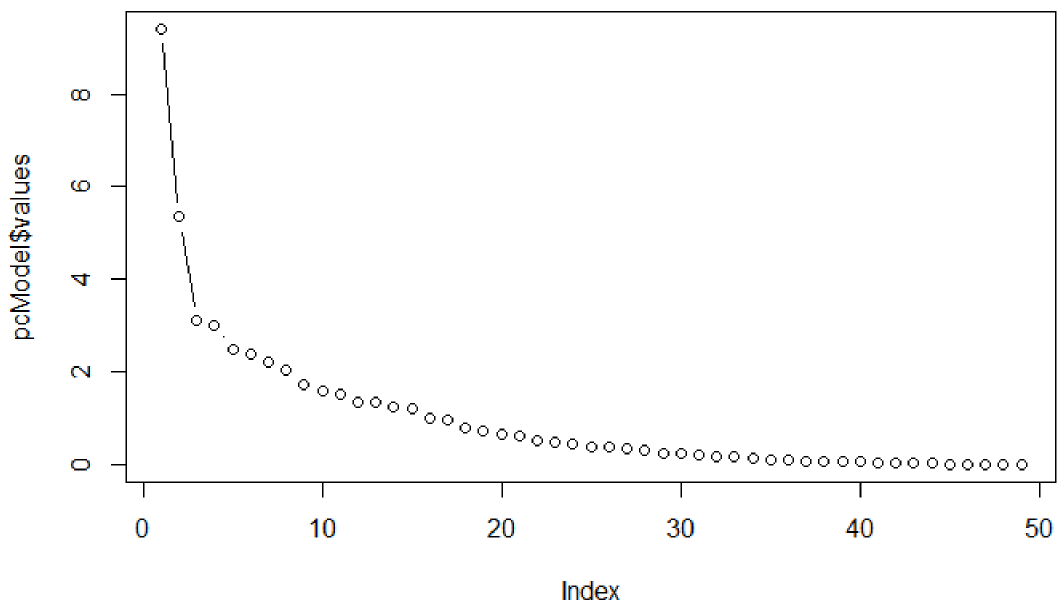
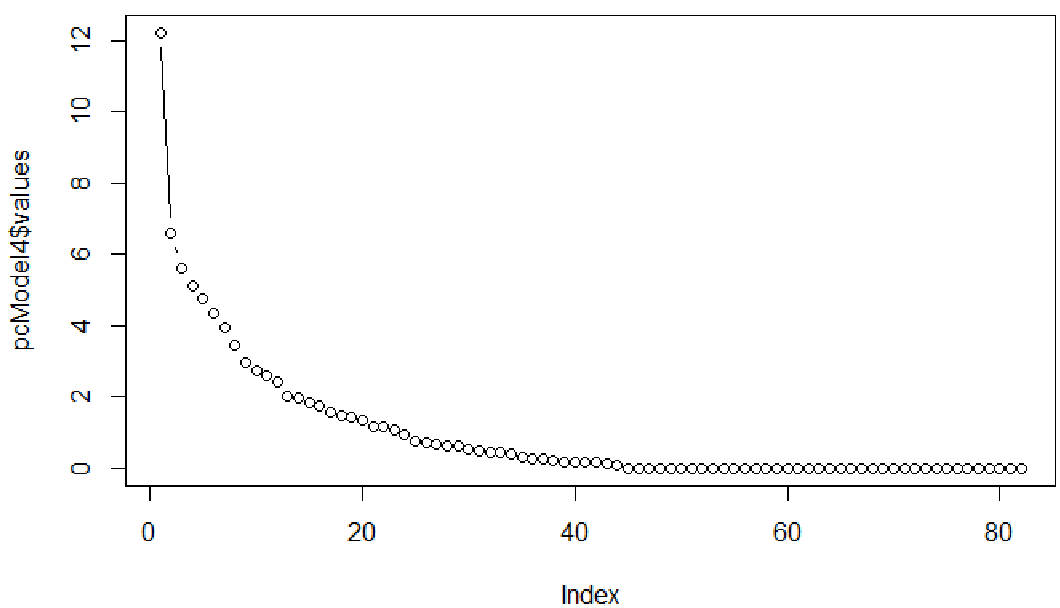


Figure B2

Twitter Scree Plot



Instagram Components

Cues With >.40 Loadings

Component 1
Attractive
Stylish
Less Images without people
Neat
Posed
Less anonymous username
Less Imbedded text
Less Pertaining to Movies/TV
Positive Facial Expression
Smiling
Dominant facial expression/pose
Less Images of inanimate objects
More followers
More Selfies

Component 2
Less neutral facial expression
Positive facial expression
Smiling
Images of self with others
Less Negative facial expression
Less selfies
Less Dominant facial expression/pose
Pertaining to sports/fitness
Neat

Component 3
Less anonymity in bio
Specific locations in Bio
Personal Bio
Bio/username emojis
Dominant facial expression
Bio word count
Pertaining to Academics

Component 4
Profile picture not of owner
Anonymity in profile picture
No bio

Component 5
More videos
More pertaining to music
More links to other SNS
More photos of inanimate objects

Component 6
More posts
More pertaining to politics
More followers

Component 7
More swear words
More pertaining to art
More inanimate objects
More animals

Component 8
More following
More pinned stories
More followers

Component 9
More candid
More pertaining to sports/fitness

Component 10
More images of only others
Less anonymity in username (besides name)
Less selfies

Component 11:
More crowds
More outdoors
More anonymous user name (besides name)

Component 12:
Includes more of name
More imbedded text

Component 13:
More pertaining to work

More pertaining to academics

Component 14:
Less academics
Less religion

Component 15:
Multiple posts
Less with animals

Component 16:
More unique others across posts

Twitter Components

Cues With >.40 Loadings

Component 1
Gratitude
Optimism
Achievement
General positivity
Less general negativity
Candid
Less anger
Under 10 RT
More diverse others
More images of only others seemingly known
More videos
More 10-100RT

Component 2
Posed
Neat
Stylish
Attractive
Less art
Profile picture less anonymous
Less memes
Less mages without people
Less neutral facial expression
Smiling
More positive facial expression

Component 3
Neutral facial expression
Dominant facial expression
Negative facial expression
Less positive facial expression
Initialisms

Component 4
More media
More tweets
More following
More followers
More bio emojis

Component 5
Less original tweets
More retweets
10-100k RT
Longer on twitter

Component 6
Less romantic relationships
Name less anonymous
Stress/anxiety
Less music
Less sexual content
Less sexually explicit words
Academics

Component 7
More likes on og tweets
More retweets on og tweets
More replies on og tweets

Component 8
Less under 10 RT
Images of others celebrities/memes
More images in feed
More mentions of specific unknown others
Less mentions of known others

Component 9
Memes
Humor
Sarcasm
Less 100-1k RT
Non-romantic relationships
Sexually explicit words
Exaggerated spellings

Component 10
Anger
Generic others
Work

Politics
Nonromantic relationships

Component 11
Less anonymous bio
Hobbies/interests
Links to other sns
Personal bio
Less sadness

Component 12
Less movies/tv
Having a banner photo
Less typos/spelling errors

Component 13
More images in feed
Less 100-1k RT
Emojis
Images of only others seemingly known

Component 14
No identifying info in username
Sexually explicit words
Exaggerated spellings

Component 15
Less academics
Bio word count
Religious content

Component 16
Profile type 1
Swear words
Initialisms

Component 17
Less videos
Less +100k RT

Component 18
Less spelling errors
No identifying info in username

Component 19
Less location specificity
No birthday

Component 20
Less 10-100 RT
1-10k RT

Component 21
Less likes

Component 22
Less hobbies/interests
Selfies

Component 23
Less exaggerated spellings
No pinned tweet
Images of self with others

Appendix C

Training Video Transcript

0:00

Hello!

0:01

The goals of this training are for you to 1) understand the personality traits known as openness and conscientiousness, 2) to learn the cues on Twitter profiles that are connected to these personality traits, and 3) to use these cues to make more accurate impressions of the personalities of others, based on their Twitter profiles. Let's get started.

0:25

To give you some context, we've done research on how people with different personalities act on Twitter, and have identified some cues that relate to personality traits. Cues are indicators, signals or hints about something, in this case, the personality of Twitter users. Some of these cues aren't intuitive and might not make sense, meaning you wouldn't think to look for them. We're going to focus on cues for two specific personality traits, openness and conscientiousness.

0:54

Openness is also called openness to experience and open mindedness. People high in openness are curious, deep thinkers, artistic, imaginative, creative, and original. People low in openness are the opposite of these things, and tend to be more conventional, traditional, rigid, and closed minded. Now let's look at the cues on Twitter for the trait of openness.

1:25

Note that these cues include both original tweets or posts that the profile owner wrote themselves and retweets or posts that were written by someone else, and reposted by the profile owner on their page. People high in openness, tend to post more pictures, or retweet more tweets with pictures in them. People high in openness tend to have less content on their page about romantic relationships, and less about sex. People high in openness also use less acronyms or initialisms, such as LOL or OMG. People low in openness on the other hand, post less pictures. People low in openness also have more content about romantic relationships and sex. People low in openness also use more acronyms and initialisms like LOL, and OMG.

2:21

Let's look at some examples. It doesn't matter here that you can't zoom in to read these profiles because it's easy to compare the amount of images. The person on the left is higher in openness and his posted more pictures. The person on the right is lower in openness and it's posted much fewer pictures.

2:39

Here we can see two tweets. On the top we have a tweet that has nothing to do with sex or romantic relationships. There are also no acronyms or initialisms. In this tweet, this person is higher in openness. On the bottom we have a tweet that is about romantic relationships and sex, and also contains four different acronyms - idk, tbh, gf, and smh. This person is lower in openness.

3:07

Moving on to the trait of conscientiousness, people high in conscientiousness are organized, responsible, systematic, persistent, hardworking, and reliable. People low in conscientiousness, are the opposite of these things - more disorganized, irresponsible, and also tend to be more laid back.

3:30

Let's look at the cues on Twitter profiles that relate to conscientiousness. Again, remember this includes original tweets and retweets. People high in conscientiousness, have more content about or referring to general groups of other people, people high in conscientiousness, use more swear words and more sexually explicit words. People high in conscientiousness, also talk less about hobbies and interests that do not fall into the categories of sports, music, TV or movies and art. We'll talk more about what this means in a moment. People low in conscientiousness, on the other hand, talk less about general groups of other people. People low in conscientiousness use less swear words and less sexually explicit words, and people low in conscientiousness talk more about hobbies and interests that are not sports, music, TV or movies, or art.

4:27

Let's look at some examples. On the left are tweets by someone higher in conscientiousness, and on the right are tweets by someone lower in conscientiousness. The tweets have similar themes, but the tweets by the more conscientious person, the person on the left, have more swear words and sexually explicit words, while the tweets by the less conscientious person, the person on the right, have no swears, or sexually explicit words. Additionally, we can see the difference in referring to general groups of people. Let's look at the first tweet. The more conscientious person refers to a general group of a-holes, while the less conscientious person refers to a specific "some jerk". Let's look at the next one. The more conscientious person refers to a general group of Seahawks fans, while the less conscientious person refers to a specific famous Seahawk player, and tags their profile indicated by the At-sign in the blue text. And in the third tweet, the more conscientious person refers to quote "the girls" as a general group, while the less conscientious person refers to a specific person she knows by name. Again, more conscientious people refer to general groups and use more explicit words, while less conscientious people refer to general groups less and use less explicit words. Let's look at the final cue for conscientiousness, which has to do with hobbies and interests. More conscientious people tweet less about hobbies and interests that are not sports, music, movies, or TV or art. This does not necessarily mean that more conscientious people tweet more about sports, music, movies, or TV or art. But if they are talking about hobbies or interest, they tend to fall into these categories. Less conscientious people, on the other hand, tweet more about hobbies and interests that are outside of these categories. Here are some examples. On the right, we see some hobbies and interests that less conscientious people might tweet about, such as video games, cooking, and traveling. These are just some examples. Any hobby or interest that is not sports, music, movies, or TV or art might be a cue for lower conscientiousness. Again, throughout these examples, the more conscientious people use more explicit words and swear words. Take a minute to look at these tweets.

7:01

Finally, it is important to note that these cues reflect the trends that we observed, but are not always perfect. One instance of a cue for example, a single swear word on a Twitter profile, does not necessarily mean that that profile owner has an extreme level of that trait, for example, the highest possible level of conscientiousness. These cues are meant to help you calibrate your impressions, and add to your knowledge of people and personality in order to make accurate impressions. Let's quickly review.

7:32

Openness refers to a trait that includes being curious, creative and original. More open Twitter users tend to post more pictures, talk less about romantic relationships and sex and use less acronyms or initialisms. Conscientiousness is a trait that refers to being more organized, hardworking and reliable, more conscientious Twitter users talk more about general groups of other people. They use more swears and sexually explicit words. And they talk less about hobbies and interests that are not sports, music, TV or movies and art.