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FULL PAPER

Can I confidently guess who you are?
Personality and intelligence perception in online dating

Weiß ich sicher, wer du bist?
Persönlichkeits- und Intelligenzwahrnehmung im computervermittelten Speed-Dating

Maximilian T. P. von Andrian-Werburg, Dorothea C. Adler, Frank Schwab, Sascha Schwarz & Benjamin P. Lange

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Abstract: We conducted two computer-mediated speed dating studies to evaluate personality perception based on language use in online dating and analyzed the data with Bayesian statistics. In each study, participants first reported mating-relevant personality traits (Big Five, sociosexual orientation) and we assessed their intelligence (N_1 = 186, N_2 = 618). Subsequently, we conducted computer-mediated speed dating sessions at our laboratory (n_1 = 56, n_2 = 94). After the first chat, participants rated their chat partner on the constructs mentioned above (i.e., personality and intelligence). Linguistic patterns in the chats were analyzed using LIWC. In both studies, consistent evidence showed that online daters systematically rated partners with higher IQ and extraversion scores as more intelligent and extraverted above chance. We also derived different linguistic cues as potential mediators from earlier studies. Empirical evidence proved very strongly against mediation based on such linguistic cues. Hence, although people are able to make correct inferences about the personality and intelligence of potential mates in the dynamic setting of speed dating, it remains unclear which cues they rely on.

Keywords: Online dating, computer-mediated communication, personality perception, Brunswick's lens, Bayesian data analysis.

Zusammenfassung: Wir führten zwei computervermittelte Speed-Dating-Studien durch, um die Persönlichkeitswahrnehmung auf Grundlage des Sprachgebrauchs beim Online-Dating zu untersuchen. Die Daten wurden mittels bayesianischer Statistik ausgewertet. In jeder Studie wurden zunächst partnerwahlrelevante Persönlichkeitsmerkmale (Big Five, sozio-sexuelle Orientierung) der Versuchspersonen erhoben; außerdem wurde deren Intelligenz gemessen (N_1 = 186, N_2 = 618). Anschließend führten wir in unserem Labor computervermittelte Speed-Dating-Sitzungen durch (n_1 = 56, n_2 = 94). Nach dem ersten Chat bewerteten die Teilnehmer*innen ihren Chatpartner auf Basis der oben genannten Konstrukte (d. h. Persönlichkeit und Intelligenz). Die linguistischen Variablen aus den Chats wurden mittels LIWC analysiert. In beiden Studien wurde ein konsistenter Beweis dafür gefunden, dass Teilnehmer*innen an Online-Dating ihre Partnerinnen und Partner auch als überzufällig extrovertierter und intelligenter einschätzten, je höher oder niedriger diese auf den jeweiligen Skalen lagen. Auf Basis vorheriger Studien wurden verschiedene sprachliche Hinweisreize als potenzielle Mediatoren, die der korrekten Einschätzung zugrunde liegen könnten, getestet. Die empirische Evidenz sprach sehr stark gegen die Mediation durch diese Hinweisreize. Das heißt: Obwohl Menschen in der Lage sind, im dynamischen Umfeld des Speed-Datings korrekte Rückschlüsse auf Persönlichkeit und Intelligenz potenzieller Partner zu ziehen, bleibt unklar, auf welche sprachlichen Hinweisreize sie ihr Urteil gründen.

Keywords: Online-Dating, computervermittelte Kommunikation, Persönlichkeitswahrnehmung, Brunswick's lens, Bayesianische Statistik.

1. Introduction

The establishment of the Internet and, later on, the emergence of different forms of social media has drastically changed human communication, interaction (e.g., Ling & Baron, 2013; Sproull & Kiesler, 1986; Walther, 2007), and thus, mating as well (e.g., Finkel, Eastwick, Karney, Reis, & Sprecher, 2012).

Indeed, online dating has become a billion-dollar business (Sautter, Tippett, & Morgan, 2010, p. 556). In 2013 in the US, for example, it replaced the intermediation of friends as number one source to find a suitable mate (Rosenfeld, Thomas, & Hausen, 2019). Therefore, online dating is one of the most obvious innovations caused by the transition from the analog to the digital era and has received considerable research interest (e.g., Valkenburg & Peter, 2007). Consequently, computer-mediated communication (cmc) is not only increasingly influencing core parts of human life, but, furthermore, also human mating as an important part of social life (Buss, 2003).

Personality characteristics are crucial in mate choice (e.g., Buss & Barnes, 1986; Botwin, Buss, & Shackelford, 1997). Numerous studies conducted throughout the last decades found that people prefer a mate who is (among other things) kind, understanding, stable, and intelligent (e.g., Lange, 2012).

In real life, potential partners have access to a dynamic set of information, like many verbal (e.g., Lange, Hennighausen, Brill, & Schwab, 2016) and nonverbal cues (e.g., touch and smell) in order to assess the respective traits of a potential partner. However, all spoken verbal and paraverbal cues are missing in cmc (Culnan & Markus, 1987; Sproull & Kiesler, 1986). Therefore, users of online dating services have to rely on rather static (e.g., written) verbal cues, if they want to further advance a relationship (Finkel, Eastwick, & Matthews, 2007).

Based on the above-mentioned explanations, the first yet understudied question arises, if relevant personality characteristics including intelligence may be inferred from reduced cmc cues in online speed dating only.

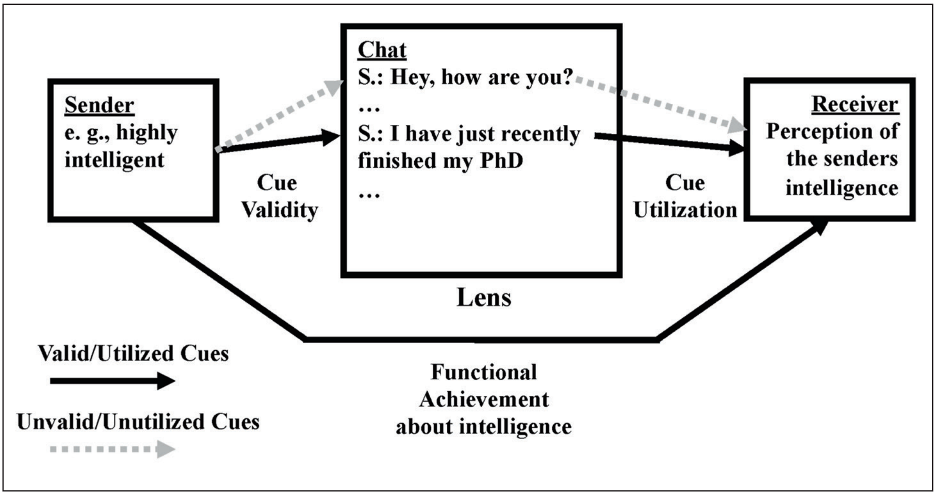
Second, humans evolved to communicate face-to-face, among other types of communication by means of spoken language (e.g., Kock, 2004), and thus, also human mating naturally occurs face-to-face (e.g., Lange, 2012). If these natural cues are used to form an impression of the communication partner and, thus, also of a potential romantic partner and if cmc lacks many of these cues (e.g., Sproull & Kiesler, 1986), the second yet understudied question arises, as to which specific cmc cues people use to make adequate judgments of potential romantic partners in online speed dating.

2. Brunswik's (1956) lens model

One theoretical framework that allows for an examination of both questions mentioned above is Brunswik's (1956) lens model. The *lens model* has been used in research on personality impression in general as well as in cmc research in particular (e.g., Gosling, Jin Ko, Mannarelli, & Morris, 2002; Hall, Pennington, & Lueders, 2014; Hinds & Joinson, 2019). It is suitable to structure the process of how different kinds of behavioral residuals (e.g., room settings; Gosling et al., 2002; digital footprints; Hinds & Joinson, 2019) created by an unaware sender are used by a receiver to make inferences about the sender. Thus, the lens model is useful to describe which cues of the target (e.g., personality and intelligence of a potential mating partner) are used by the receiver to form an impression of the target's traits (e.g., personality and intelligence).

In the terminology of Brunswik's (1956) model, behavior residuals constitute the *lens* through which a receiver perceives a sender. Other important terms are (1) *cue validity* and (2) *cue utilization*. Cue validity exists if (some) behavior residuals are actually related to certain traits of the sender. Cue utilization takes place, if a receiver actually uses behavior residuals for inferences about the sender, irrespective of whether these residuals are actually related to the sender's traits. A *functional achievement* is finally reached, if cues are (1) *valid* and (2) *utilized* to make a credible judgment about the sender.

Figure 1. Brunswick's (1956) lens model adapted to cmc



Note. In this example, the receiver correctly infers the high intelligence of the sender from the semantic information that the sender has just currently finished his PhD (a behavior residual for intelligence).

Figure 1 visualizes the lens model as applied to online speed dating and gives an example for a functional achievement for intelligence. In Figure 1, a sender tells a receiver that she/he has just finished a PhD. This is a semantic (valid) cue for intelligence that the sender (theoretically) utilizes to make an inference about her/his opposites personality. More general, in Figure 1 the content of an online speed dating chat becomes the *lens* through which a receiver indirectly perceives the personality and further relevant traits of a sender.

3. Previous empirical research about personality perception in cmc

Most studies only examined either the question of how cmc cues of the sender reflect her/his personality (cue validity) or if the receiver uses cues to make judgments about the other person (cue utilization).

For example, research on cue validity has been conducted by Hirsh and Peterson (2009) who analyzed texts of 94 student authors with the text analysis software Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, Boyd, & Francis, 2015). They found linguistic correlates for each of the Big Five factors (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism). For instance, openness to experience was correlated to the number of perceptual words, while neuroticism was related to words indicative of negative emotions (for a full list see Hirsh & Peterson, 2009, p. 526).

Schwartz et al. (2013) also conducted a LIWC analysis and showed by investigating the messages of approximately 75,000 volunteers that gender, age, and personality were correlated to a huge number of linguistic variables (regression effects ranging from $\beta = -.17$ to $\beta = .15$), among them personal pronouns, plural, and conjunctions as well as affect-related words (for a full list see Schwartz et al., 2013, p. 7). Therefore, several linguistic variables exist that could be used as valid cues with respect to key dimensions of human personality.

On the receiver side, cue utilization seems to take place. For instance, people are able to correctly guess the gender of a person as well as her/his personality and her/his mating strategy with above-chance accuracy solely based on the linguistic material the respective person has produced (e.g., Back, Schmukle, & Egloff, 2008; Heisler & Crabill, 2006; Koch, Mueller, Kruse, & Zumbach, 2005; Lange, von Andrian-Werburg, Adler, & Zaretsky, 2019; Lange, Zaretsky, & Euler, 2016; Savicki, Kelley, & Oesterreich, 1999; Thomson & Murachver, 2001).

Some studies even identified a functional achievement. For example, in online dating ads, the mating-relevant personality trait extraversion was detected with above-chance accuracy (Weidman, Cheng, Chisholm, & Tracy, 2015). Furthermore, in a meta-analysis Tskhay and Rule (2014, p. 28) showed that accuracy effects for the Big Five traits extraversion (9 studies, $M_{Zr} = .33$, 95% CI = [.01, .65]), and conscientiousness (8 studies, $M_{Zr} = .11$, 95% CI = [.01, .20]) were positive in size and significant. Therefore, strong evidence exists that personality can be correctly inferred from written communication. However, all (analyzed) studies relied on static verbal descriptions of the sender. Whether these results also apply to more dynamic, interactive contexts (like speed dating), remains to be answered.

Therefore, the objective of our research was, as previously mentioned, (1) to investigate, whether people are able to appropriately guess the personality of a chat partner only from a written chat during a dynamic real-world speed dating, and (2) to identify linguistic mediators for correct inferences about a counterpart's personality. Those mediators should constitute parts of the lens between the sender's personality and the receiver's perception of it (see Figure 1). We therefore aimed to theoretically derive cues and empirically test them as (manifest) mediators for the judgments of (latent) personality factors. To address these objectives, we set up three hypotheses and one research question.

4. Hypotheses and research questions

4.1 Hypotheses: Personality and intelligence can be correctly guessed in online speed dating

In previous studies, the Big Five model of personality was used in mate choice research. All Big Five dimensions seem to be very decisive in this area of social life (e.g., Botwin et al., 1997) and we expect that daters pay close attention to them. Therefore, our first hypothesis is:

> *H1: People are able to guess an online dating chat partner's personality factors (Big Five):*
>
> *H_{1a}: Openness*
>
> *H_{1b}: Conscientiousness*
>
> *H_{1c}: Extraversion*
>
> *H_{1d}: Agreeableness*
>
> *H_{1e}: Neuroticism*

However, not only are the personality dimensions of the Big Five crucial in mate choice; there is an abundance of empirical research that intelligence is, too (e.g., Fisman, Iyengar, Kamenica, & Simonson, 2006). Escorial and Martín-Buro (2012), for instance, showed that individuals seem to put strong emphasis on finding an, at least, equally intelligent mate. This can be related to the principle of homogamy which "is based on the suggestion that people couple with partners who match their basic personality and phenotypic traits" (Štěrbová & Valentová, 2012, p. 48). Hence, we set up the next hypothesis as follows:

> *H2: People are able to estimate the IQ of a chat partner.*

Beyond personality, knowing the other's mating strategy, sometimes termed sociosexual orientation, is important, too. Sociosexual orientation indicates, if someone is pursuing a short-term (affair, one-night stand, etc.) or rather a long-term (committed, steady relationship) mating strategy (Penke & Asendorpf, 2008; Simpson & Gangestad, 1991). The individuals' mating strategy has implications for relationship functioning as well. Individuals with an unrestricted (= short-term) sociosexual orientation are, for example, less committed to their relationships and more likely to engage in infidelity (Mattingly, Clark, Weidler, Bullock, Hackathorn, & Blankmeyer, 2011). Thus, it is reasonable to assume that perceivers seek cues to a respective individual's sociosexual orientation as well. Lange et al. (2019), for example, have already shown that a short nickname in online dating already allows for valid judgments of personality – among other traits (Big Five, narcissism) of one's sociosexual orientation. Expanding on the findings by Lange et al. (2019), we expected that sociosexual orientation can also be detected from a written, more dynamic speed-dating chat:

> *H3: People are able to estimate an online dating chat partner's sociosexual orientation.*

4.2 Research question: Linguistic cues to reach functional achievement in personality perception

Furthermore, as suggested by previous research (e.g., Lange et al., 2019), we expected that chatters are able to reach functional achievement (Brunswick, 1956) and, thus, that personality perception is mediated through written language. Therefore, we formulated a corresponding research question:

> *RQ1: Which cues cause the (potential) functional achievements between reported and estimated personality traits and IQ?*

As potential cues for correct Big Five judgments, we opted for LIWC variables that represent valid cues as identified by Hirsh and Peterson (2009) (e.g., "social processes") and Schwartz et al. (2013) (e.g., "sexual"). We further included variables that accounted for a functional achievement in the research of Hall et al. (2014) in case they were applicable to our setting and a part of the LIWC dictionary (e.g., the LIWC category "Positive Emotion" for Hall's et al., 2014, category "status update positive affect", which is related to extraversion). As the relationships between the LIWC variables and the respective personality traits in the research of Schwartz et al. (2013) were rather small and numerous, we further decided to only include variables from that research with β coefficients that equaled or exceeded .10, as this is only half the value one would deem a small effect (Cohen, 1988). We also chose the linguistic cues that consistently appeared in both studies of Weidman et al. (2015), for instance the LIWC category "word count".

For IQ, we further chose the following variables (abbreviations of the names of the LIWC categories in parentheses): word count (WC), words per sentence (WPS), percentage of words longer than six letters (Sixltr). WC measures the quantity of linguistic code, WPS morphosyntactic/grammatical complexity on the sentence level, and Sixltr complexity on the word level as well as word frequency. All those measures have been shown to correlate with intelligence (e.g., Kanazawa, 2006; Kemper & Sumner, 2001; Schwarz & Hassebrauck, 2012; Lange, Zaretzky, et al., 2016; Wechsler, 1958).

As potential cues for correct sociosexual orientation judgments, we opted for the LIWC category "sexual." The relationship between the Big Five on the one hand and sexual behavior and attitudes on the other hand has already been discussed and was, furthermore, supported by previous research (Barnes, Malamuth, & Check, 1984; Heaven et al., 2003; Schmitt, 2004). To be precise, Barnes et al. (1984) and Heaven et al. (2003) found that mostly extraversion, but also other facets of the Big Five correlated with the frequency of and attitudes towards sexual behavior. For this reason, the same linguistic variables used for the Big Five were also planned to be employed for the investigated judgment of sociosexual orientation.

5. Method

We conducted two studies with independent non-exclusively academic samples in Germany. Each study consisted of two steps. In step one, each participant completed an online questionnaire and in step two, participants were invited to a cmc speed dating session in our laboratory.

Sample Study 1. Of the N_1 = 189 participants (100 female, M_{age} = 27.81 years, SD_{age} = 7.77 years) who completed the online questionnaire (step one), n = 57 attended the speed dating sessions (step two). Of these, one had to be excluded because it was impossible to match their data from the speed-dating session to the corresponding online questionnaire. The final sample consisted of n_1 = 56 participants (29 female, M_{age} = 26.79 years, SD_{age} = 6.32 years). Of these participants 7 reported to have a secondary school certificate, 28 a high school and 20 a university/college degree. One participant reported holding a different (and unspecified) kind of degree.

Sample Study 2. For Study 2, N_2 = 616 participants (336 female, 277 male, 3 other, M_{age} = 27.31 years, SD_{age} = 7.93 years) participated in the online questionnaire (step one). Of these, n_2 = 94 (48 female, 46 male) participants attended the speed-dating session (step two). Four participants had to be excluded prior to the analyses, because it was impossible to match their data from the speed-dating session to the corresponding online questionnaire. The average age of the participants was 26.47 years (SD = 6.51 years). Eight participants reported to have a secondary school certificate, 49 a high school and 34 a college/university degree. One participant reported a qualification below secondary school certificate education and two different kinds of degrees.

5.1 Measures Study 1

The personality traits assessed via the online questionnaire, relevant for this paper[1], were the Big Five (Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2013) and sociosexual orientation (Penke & Asendorpf, 2008). Furthermore, we asked for standard demographic variables like age, gender (male, female, and other), and sexual orientation. Prior to the speed-dating sessions on site, we assessed the IQ (general intelligence) of each participant with a number connection test (Oswald & Roth, 1987). After the first speed dating chat session, we asked participants to rate their respective chat partner on the personality scales used in step one, but we

1 An overview of all used measures in both studies and all measures that can be passed on without copyright issues can be obtained from the corresponding author.

reformulated all items from the first to the third person. According to Penke and Asendorpf (2008) sociosexual orientation can be assessed globally by averaging all nine items of their instrument (SOI-R) or in components (attitude towards sociosexuality, sociosexual behavior and desire). We assessed global sociosexual orientation with the highest loading item for each of the three components in order to keep the time for completing the questionnaire to a minimum. By asking the participants to rate the chat partner's IQ, we assessed the estimated IQ with one item. We provided the information that an average person has an IQ of 100 and that values below 70 or above 130 would each only apply to 2% of the population. For personality and intelligence assessments we opted for relatively short scales in order not to fatigue our participants (cf. Weidman et al., 2015). A complete overview of measures used in Study 1, relevant for this paper, is shown in Table 1.

Table 1. Relevant measures in the different steps of study 1 and study 2

	Measures Study 1		Measures Study 2	
Variables	Step 1	Step 2	Step 1	Step 2
Big Five	BFI-10[1]	BFI-10[1]	BFI-2[5]	BFI-10[1]
IQ	ZVT[2]	Open question[4]	HMT[6]	Open Question[4]
Sociosexuality	SOI-R[3]	SOI-R[6]	SOI-R[3]	SOI-R[3]

Note. [1]Rammstedt et al. (2013); [2]Oswald & Roth, 1987; [3]Penke & Asendorpf, (2008); [4]single question developed by the authors; [5]Soto & John, (2017); 6 SOI-R[3] consists of 3 components (attitude, behavior, desire), we measured global sociosexuality with the highest loading item of each component.

5.2 Measures Study 2

Study 2 is mainly based on Study 1, however, with some methodological enhancements. First, instead of the number connection test we used the Hagen Matrices Tests (HMT; Heydasch, 2014) to assesses general intelligence more reliably compared to the previously used number connection test. The HMT was completed by our participants in the online questionnaire prior to the on-site speed dating sessions.

We also included all nine items that measured sociosexuality reformulated into third person. Furthermore, we used a more sophisticated measure for the Big Five (Soto & John, 2017) in the online questionnaire compared to Study 1. However, since we still had limited time only in the laboratory, we again used the 10-item short scale of Rammstedt et al. (2013) reformulated to the third person after the online speed dating sessions. An overview of all used measures, relevant for this paper, is shown in Table 1.

5.3 Data collection Study 1

After completion of the online questionnaire, we assigned the potential participants to certain speed dating sessions with regard to approximately the same age and time availability. Up to 8 people (4 male, 4 female) were invited to the respective online speed dating event. In the laboratory, the participants – seated at separate computers and shielded with office cubicles – chatted with people of the opposite sex for 8 minutes without seeing or hearing each other (regular speed-dating sessions have a fixed duration; dependent on the individual setting they last between 3 and 8 minutes; Finkel et al., 2007). In our setting, a separate online chat room was provided for each pair. After the 8 minutes ended, participants were either forwarded to the questionnaire about their chat partner or to a page that simply stated that they had to wait for further instructions. The speed dating chat logs were saved after each session for linguistic analysis using the current German version of LIWC (Pennebaker et al., 2015; Wolf et al., 2008). We only evaluated opposite personality ratings after the first chat session, as we expected a habituation effect and biased communication behavior in the subsequent dyads.

5.4 Data collection Study 2

In Study 2, we increased the length of the speed-dating sessions up to 10 minutes because in Study 1 it seemed that 8 minutes was too short to have a proper conversation in some cases. However, the basic data gathering procedures remained unchanged compared to Study 1.

5.5 Data analysis

All analyses were conducted with R 3.6.3 (R Core Team, 2020). To evaluate the hypotheses and the research question we decided to use a Bayesian instead of a Frequentist approach as (1) the number of tested hypotheses in a Bayesian analysis is neglectable as long as the data is relevant for the hypotheses and research questions (Dienes, 2011), (2) a Bayesian approach also allows to reasonably assess null hypotheses (Dienes, 2014) and (3) it is possible to use empirically informed priors (Zyphur & Oswald, 2015).

Missings. For both studies, Little's MCAR test indicated that missing data occurred completely at random for the personality and IQ variables (Study 1: p = .18, Study 2: p = .17). Variables derived from LIWC had no missing values and were not included in Little's MCAR test. We used non-parametric random forest imputation (1000 trees) to obtain a complete dataset (Stekhoven & Bühlmann, 2012).

Bayes factors vs. posterior probability. For the decision as to whether a hypothesis was meaningful, we used Bayes factors instead of posterior distributions, as Bayes factors are more appropriate to ascertain the presence or absence of a hypothesized effect compared to posterior distributions (Dienes, 2014; Doorn et al., 2019). However, if we considered a hypothesis meaningful, we also calculated relating posterior distributions.

Hypotheses and verbal labels of Bayes factors. All hypothesis tests evaluate, if there is either no relationship (H_0) or if there is a positive relationship between the respective constructs (H_1). For tests regarding non-independence and the research question, H_1 only assumes that an effect exists. To verbally describe the Bayes factors, we used the labels provided by Jeffreys (1961) with the adjustments of Lee and Wagenmakers (2013). Accordingly, a Bayes factor (BF_{10}, which reads "H_1 (a (positive) effect exists) over H_0 (no effect exists)") of 1 provides *no evidence*, factors between 1-3 provide so-called *anecdotal evidence*, between 3-10 point to *moderate*, between 10-30 to *strong*, between 30-100 to *very strong* and above 100 to *extreme* evidence for a (positive) effect. In the opposite direction, a BF_{10} between 1 and ⅓ provides *anecdotal* evidence that there is no effect (H_0), between ⅓ and $1/_{10}$ provides *moderate*, $1/_{10}$ and $1/_{30}$ *strong*, $1/_{30}$ and $1/_{100}$ *very strong* and below $1/_{100}$ provides *extreme* evidence for H_0.

Priors. First, we used the weakly informative Jeffreys-Zellner-Siow prior developed by Liang, Paulo, Molina, Clyde and Berger (2008) implemented in the *jzs_cor* function (BayesMed, v. 1.0.1; Nuijten, Wetzels, Matzke, Dolan, & Wagenmakers, 2015) to calculate Bayes correlations for both studies (for a detailed discussion of the hypothesis test, see Wetzels & Wagenmakers, 2012). We opted for this procedure to initially display the linear trends within each data set. However, if an alternative hypothesis received enough empirical evidence to be consistently considered as at least anecdotal, we graphically displayed the respective relationship. To do so, we calculated a Bayes regression with the weakly-informative default priors based on normal distribution for intercepts and coefficients and on the exponential distribution for σ of the *stan_glm* function (rstanarm, v. 2.19.2; Goodrich, Gabry, Ali, & Brilleman, 2019), which *means (M)* and *scales (s)* or respective *rates* will be reported for each analysis in the results section. We further used median (*Mdn.*) and median absolute deviation (*MAD,* basically a robust standard deviation) from the respective effect of Study 1 as priors for the slope/effect of Study 2. Therefore, one has to be careful not to interpret the linear models presented below to be a result of the data of Study 2 independent of Study 1. Finally, we used the Jeffreys-Zellner-Siow prior for the mediation analysis with the *jzs_med* command as we did with *jzs_cor* (BayesMed, v. 1.0.1; Nuijten et al., 2015).

Explanation of further used terms. Further terms used in the analyses below that need explanation are *CI*, which is the abbreviation for Bayesian credibility interval, and *Overlap*. A Bayesian *CI* expresses a certain range of the posterior distribution and gives an overview of the area in which an empirical effect can fall to a certain probability (e. g., 95%). The term *Overlap* describes the probability that a value from the posterior distribution of a slope/effect comes from an equal uncertain (equal *MAD*) null distribution.

Non-independence. Our participants interacted within a dyad while speed dating. In this dyad different factors like the common experience our participants shared can cause a statistical dependency of the variables assessed during or after speed dating (Kenny, Kashy, & Cook, 2006). However, we did not evaluate a "classic dyadic design" as the online self-reports of step one causally preempted the personality estimates of step two and, thus, could not have been affected by the dyadic interaction in any way. Within the speed datings (a given dyad), we quantified the degree of non-independence (the amount of similarity) as described by Kenny et al. (2006) for the opposite personality ratings and computed a Bayesian fixed effects model with a weakly-informative Cauchy prior distribution that included all effects of personality and intelligence from both studies (Mdn = 0, s = $1/_{\sqrt{2}}$). The aggregated effect was d = –.04, 95%CI = [-0.14; 0.06], k = 14, BF_{10} = 0.08. Therefore, it is about 12.2 times more likely that there is no non-independence than vice versa. Finally, we quantified the degree of non-independence for both studies of the linguistic cues that were relevant for the calculated mediations below. Unsurprisingly, the use of these cues is, on average, related within each dyad with extreme evidence (we used the same method as above, d = 0.29, 95%CI = [0.20; 0.38], k = 15, BF_{10} > 100). However, we did not deem this as a bias because it is only natural and ecologically valid that communication partners linguistically adapt to each other during an ongoing communication (Niederhoffer & Pennebaker, 2002). We, therefore, did not conduct further steps to control for non-independence.

6. Results

6.1 Hypothesis 1a: Openness

We calculated Bayesian correlations between self-reported and estimated openness using the data from Study 1 (r = .14, BF_{10} = 0.33) and Study 2 (r = .23, BF_{10} = 1.95). BF_{10} of Study 1 provides anecdotal evidence for H_{0a}. Contrarily, the data of Study 2 provides anecdotal evidence for a positive association between self-reported and estimated openness as the Bayes factor indicates that H_{1a} is about 1.95 times more likely than H_{0a} given the provided data and priors as described above. In sum, the mixed evidence still indicates that online daters are not consistently able to make estimations about the openness of their chat partners.

6.2 Hypothesis 1b: Conscientiousness

Results of the Bayesian correlation between estimated and self-reported consciousness in Study 1 (r = –.13, BF_{10} = 0.05) provide strong evidence for H_{0b}. The data obtained from Study 2 also provides strong evidence for H_{0b} (r = -0.07, BF_{10} = 0.05). Both Bayes factors indicate that H_{0b} is 20 times more likely than H_{1b}. The summarized empirical evidence leads to a clear rejection of H_{1b}.

6.3 Hypothesis 1c: Extraversion

The data obtained from Study 1 offers anecdotal evidence for H_{1c} (r = 0.24, BF_{10} = 1.01). The results of Study 2 also indicate anecdotal evidence for a positive association between reported and estimated extraversion (r = .23, BF_{10} = 2.35). We considered these results as anecdotal evidence in favor of H_{1c} and therefore conducted further analyses: The linear model of Study 1 has an explanatory power (R^2) of about 5.52% (MAD = 0.06, 90% CI [0, 0.15]). Rate for σ prior was 1.00. The intercept is at 2.36 (MAD = 0.56, 90% CI [1.45, 3.26], prior distributions M = 0, s = 9.90). The probability that a positive relationship between self-reported and estimated extraversion exists is 96.83% (*Mdn.* = 0.26, MAD = 0.15, 90% CI [0.02, 0.49], Overlap = 37.99%, prior distributions M = 0.00, s = 2.70). The model of Study 2 with the gathered information of Study 1 (Figure 2) used *Mdn.* and MAD of Study 1 as priors for the effect and has an explanatory power of about 6.21% (MAD = 0.04, 90% CI [0, 0.12]). Rate for σ prior was 1.40. The intercept

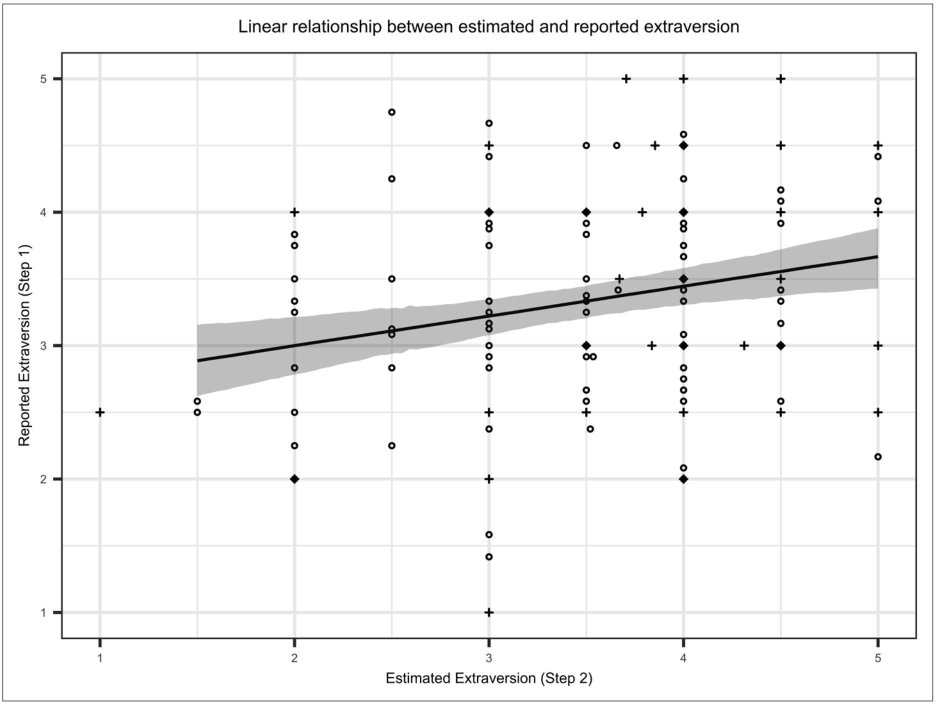
Table 2. Descriptive statistics of self-reported (step 1) and guessed (step 2) personality variables and assessed (step 1) and guessed (step 2) intelligence of study 1 ($N = 56$) and study 2 ($N = 94$)

Variables	Study 1 Step 1		Study 1 Step 2		Study 2 Step 1		Study 2 Step 2	
	M (SD)	Min./Max.	M (SD)	Min./Max.	M (SD)	Min./Max.	M (SD)	Min./Max.
Openness	3.59 (0.98)	1.50/5.00	3.40 (0.71)	1.00/5.00	3.60 (0.70)	1.58/4.92	3.42 (0.72)	1.50/5.00
Conscientiousness	3.40 (0.86)	1.50/5.00	3.68 (0.75)	1.50/5.00	3.54 (0.65)	2.17/5.00	3.59 (0.63)	2.00/5.00
Extraversion	3.33 (0.99)	1.00/5.00	3.74 (0.91)	1.00/5.00	3.33 (0.72)	1.42/4.75	3.43 (0.82)	1.50/5.00
Agreeableness	3.37 (0.75)	1.50/5.00	3.52 (0.61)	2.00/4.50	4.03 (0.44)	2.50/4.83	3.57 (0.62)	1.50/4.50
Neuroticism	2.83 (0.85)	1.50/5.00	2.37 (0.74)	1.00/4.50	2.54 (0.67)	1.08/4.08	2.42 (0.64)	1.00/4.00
IQ	112.27 (14.59)	73.00/145.00	110.32 (9.03)	75.00/125.00	114.54 (16.28)	85.00/144.00	110.46 (8.04)	90.00/132.00
Sociosexuality	4.00 (1.25)	1.22/7.00	4.39 (1.32)	2.00/9.00	3.89 (1.21)	1.67/8.11	4.15 (0.92)	2.00/6.33

Note. The table shows descriptive statistics of self-reported (step 1) and guessed (step 2) personality variables and assessed (step 1) and estimated (step 2) intelligence of study 1 (N = 56) and study 2 (N = 94). Big Five variables were assessed on a 1 to 5 scale; the scale for sociosexuality ranged from 1 to 9.

is at 2.56 (*MAD* = 0.28, 90% *CI* [2.10, 3.00], prior distributions *M* = 0, *s* = 7.20). The probability that a relationship between self-reported and estimated extraversion exists is 99.88% (*Mdn*. = 0.22, *MAD* = 0.08, 90% *CI* [0.08, 0.33], Overlap = 15.59%).

Figure 2. Linear model of extraversion



Note. Linear model with 90% *CI* of estimated and reported extraversion of study 2 with priors for intercept and slope of study 1. + is the point shape of study 1. o is the point shape of study 2.

6.4 Hypothesis 1d: Agreeableness

The Bayesian correlation between self-reported and estimated agreeableness found in Study 1 offers moderate evidence (r = .04, BF_{10} = 0.14) for H_{0d}. For Study 2, the BF_{10} was 0.94 and r was .19, which means that the data offers anecdotal evidence for H_{0d}. In sum, we see no evidence for a linear relationship between self-reported and estimated agreeableness but rather proof against it.

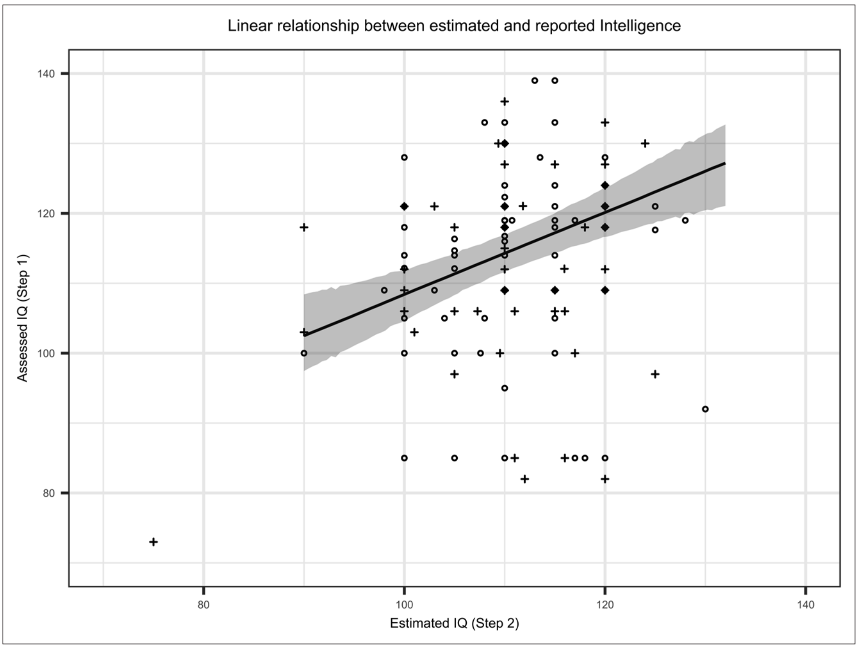
6.5 Hypothesis 1e: Neuroticism

For neuroticism, the data collected in Study 1 offers strong evidence against a positive relationship between self-reported and estimated neuroticism (r < .01, BF_{10} = 0.10). Data obtained in Study 2 also offers moderate evidence against a positive relationship (r = .05, BF_{10} = 0.13). In sum, we see no evidence that chatters were able to make inferences about the slope and/or direction of the linear relationship between self-reported and estimated neuroticism of their respective counterparts.

6.6 Hypothesis 2: Intelligence

The data collected in Study 1 offers anecdotal evidence for a positive relationship between estimated and assessed intelligence (r = .28; BF_{10} = 2.32). Very strong evidence for the mentioned relationship is further offered by Study 2 (r = .34; BF_{10} = 50.29). Hence, it seems that chatters were able to correctly guess the direction of the intelligence of their chat partner. The linear model of Study 1 has an explanatory power (R^2) of about 8.44% (*MAD* = 0.064, 90% *CI* [0, 0.180]). Rate for σ prior was 1.00. The intercept is at 60.11 (*MAD* = 22.27, 90% *CI* [26.040, 100.140], prior distributions M = 0.00, s = 146.00). The probability that a relationship being positive between assessed and estimated intelligence of Study 1 exists is 99.10% (*Mdn.* = 0.47, *MAD* = 0.20, 90% *CI* [0.130, 0.800], Overlap = 24.42%, prior distributions M = 0.00, s = 4.00). The linear model, informed by Study 1, used in Study 2 (Figure 3) has an explanatory power (R^2) of about 8.46% (*MAD* = 0.04, 90% *CI* [0.02, 0.16]). Rate for σ prior was 1.40. The intercept is at 50.15 (*MAD* = 16.44, 90% *CI* [21.05, 75.74], prior distributions M = 0.00, s = 163.00). The probability that a positive relationship between assessed and estimated intelligence of Study 2 exists is >99% (*Mdn.* = 0.58, *MAD* = 0.15, 90% *CI* [0.33, 0.82], Overlap = 4.92%).

Figure 3. Linear model of intelligence



Note: Linear model with 90% of estimated and reported IQ of study 2 with priors for intercept and slope of study 1. + is the point shape of study 1. o is the point shape of study 2.

6.7 Hypothesis 3: Sociosexual orientation

H_3 expects that online daters are able to correctly estimate their chat partner's sociosexual orientation. Results of Study 1 (r = .19, BF_{10} = 0.58) offer anecdotal evidence, results of Study 2 (r = .03, BF_{10} = 0.10) even provide strong evidence for H_0. Thus, online daters are not able to make inferences about the sociosexual orientation of their chat partners.

6.8 RQ_1: Do linguistic cues exist through which an online dater's personality is perceived?

We calculated mediation analyses with the LIWC categories: "family", "humans", "positive emotions", "sexual", "social processes" and "WC" (word count) for extraversion (Hall et al., 2014; Hirsh & Peterson, 2009; Schwartz et al., 2013;) and with the LIWC categories "WC" (word count) , "WPS" (words per sentence) and "Sixltr" (percentage of words longer than six letters) for IQ, as explained above. Descriptive statistics for the LIWC variables are displayed in Table 3.

Table 3. Descriptive statistics of LIWC variables used in the mediation analyses of RQ_1

Variables	Study 1		Study 2	
	M (SD)	*Min./Max.*	*M (SD)*	*Min./Max.*
Family	0.07 (0.25)	0/1.21	0.03 (0.14)	0/0.78
Humans	0.31 (0.45)	0/2.13	0.31 (0.51)	0/2.27
Positive Emotions	2.56 (1.92)	0/6.96	2.38 (1.90)	0/10.94
Sexual	0.06 (0.19)	0/0.76	0.08 (0.22)	0/1.10
Sixltr	15.41 (3.83)	4.60/23.97	17.14 (3.55)	6.86/25.95
Social Processes	1.61 (1.05)	0/4.35	1.34 (0.96)	0/5.07
WC	163.88 (42.37)	87.00/273.00	176.76 (63.76)	64.00/396.00
WPS	19.54 (15.61)	6.10/87.00	14.62 (9.21)	5.70/70.50

Note. WC = Wordcount, WPS = average words per sentence, Sixltr = Words with more than six letters

The results of the mediation analyses are displayed in Table 4. The respective Bayes factors (and descriptive results) mostly indicate very strong to extreme evidence against a positive mediation of extraversion through the mentioned LIWC variables. One exception is the mediation effect of WC on extraversion. The respective data basically delivers no evidence for H_1 or H_0. For IQ, there is, mostly similar, very strong to extreme evidence against our assumptions that the respective linguistic cues positively mediate the relationship between actual intelligence and the perception of intelligence.

Table 4. Standardized path and mediation coefficients of the analyses conducted to assess possible mediations between self-reported and estimated extraversion and IQ of both studies

	Extraversion						IQ		
Parameters	Family	Humans	Pos. Emo.	Sexual	Social proc.	Word count (WC)	Sixltr	Word Count (WC)	Words per sentence (WPS)
	β (BF_{10})	β (BF_{10})	β (BF_{10})	β (BF_{10})	β (BF_{10})	β (BF_{10})	β (BF_{10})	β (BF_{10})	β (BF_{10})
Study 1									
A	0.07 (0.12)	-0.15 (0.20)	0.18 (0.27)	-0.05 (0.11)	0.18 (0.27)	0.13 (0.17)	0.10 (0.14)	0.10 (0.14)	-0.22 (0.44)
B	0.12 (0.25)	0.09 (0.21)	0.24 (0.87)	0.20 (0.22)	0.24 (0.87)	0.22 (0.67)	-0.13 (0.27)	0.26 (1.52)	0.10 (0.22)
T′	0.23 (1.39)	0.25 (1.80)	0.19 (0.87)	0.24 (1.92)	0.19 (0.87)	0.20 (1.09)	0.29 (4.22)	0.25 (2.56)	0.30 (4.40)
Mediation	0.01 (0.02)	-0.01 (0.03)	0.04 (0.11)	-0.01 (0.04)	0.04 (0.11)	0.03 (0.06)	-0.01 (0.03)	0.03 (0.08)	-0.02 (0.06)
Study 2									
A	-0.08 (0.11)	-0.09 (0.12)	0.14 (0.21)	-0.09 (0.12)	-0.19 (0.45)	0.28 (3.51)	0.19 (0.47)	0.14 (0.20)	-.02 (0.08)
B	-0.15 (0.38)	0.09 (0.19)	< .01 (0.13)	0.06 (0.15)	-0.03 (0.13)	0.24 (1.93)	0.16 (0.47)	0.01 (0.13)	< 0.01 (0.13)
T′	0.22 (2.86)	0.24 (4.29)	0.23 (3.35)	0.24 (3.99)	0.22 (2.81)	0.16 (0.87)	0.30 (26.03)	0.33 (60.35)	0.33 (70.80)
Mediation	0.01 (0.03)	-0.01 (0.02)	<.01 (0.02)	.01 (0.01)	0.01 (0.04)	0.07 (1.05)	0.03 (0.11)	< .01 (0.02)	< .01 (0.01)

Note. A labels the path between the independent variable and the (potential) mediator. B is the label for the path between the mediator and the dependent variable. T' labels the direct effect.

7. Discussion

The first aim of our research was to evaluate people's ability to guess the personality of a chat partner in real world cmc speed dating. According to the terms of Brunswick's lens model (1956), we tried to evaluate, if humans are able to reach functional achievements by making correct inferences about the personality/intelligence of a cmc dating partner in a dynamic "real world" setting. Our second aim was to assess different cues that could act as manifest mediators – within the lens of the chats – for the latent functional achievements.

7.1 Which (personality) dimensions can online daters perceive?

Regarding our first aim, the data of both studies offer anecdotal evidence that online speed daters are at least able to estimate the linear trend of their dating partner's self-reported extraversion. Online daters are, furthermore, able to make inferences about a chat partner's intelligence with high probability in linear relationship to their intelligence test results. The relationships between reported and estimated openness to new experiences received mixed evidence. Because of the Bayesian approach that assesses the H_0 as well, we are further able to draw the conclusion that it is, with a very high degree of certainty, not possible to make inferences about the remaining Big Five variables and an opposite's sociosexual orientation.

The fact that the linear trend of extraversion was estimated above all other personality variables is in line with previous research. In the meta-analyses by Tskhay and Rule (2014), for example, extraversion had the highest accuracy followed by conscientiousness, which provided mixed evidence in the displayed studies. In the study by Lange et al. (2019) on online dating nicknames, extraversion was shown to be the best detectable among all personality traits as well. The study by Weidman et al. (2015) on online personal advertisements addressing potential romantic partners offers similar evidence for a relatively good detectability of extraversion. We assume that – of all personality traits – extraversion can be detected "so well", because it is the most obvious personality trait someone can experience when she/he engages in a first time conversation (Kenny, 1994). It has a strong impact on how and if someone opens up and pursues a conversation, for example.

Intelligence, as already argued, is of course an important mating trait in its own right (Escorial & Martín-Buro, 2012; Fisman et al., 2006) and as we had a relatively intelligent sample (as can be seen in Table 2), participants who acted as receivers could have been especially aware and observant of the trait. This might be related to assortative mating (e.g., Robinson et al., 2017) were our participants reached out to find a suitable mate with a relatively equal level of cognitive skill.

7.2 Linguistic cues

With regard to our second aim, we were not able to identify any linguistic cues that mediated the perception of intelligence or extraversion. As mentioned in the methods section, the reciprocal adaption to the linguistic style of the opposite chat partner (Niederhoffer & Pennebaker, 2002) might have in parts diminished the effects of a linguistic expression of personality and intelligence. This might explain the huge probability that the hypothesized variables play no part in the personality perception of online daters based on our data. Additionally, humans seem to use different (complex semantic and contextual) cues to make estimations about a counterpart's personality that are mostly not covered by the currently used LIWC dictionary (Hall et al., 2014). Even more importantly, LIWC in general (apart from the used dictionary) only investigates single words and is "blind" for all meanings above that level (for details on the features and algorithms of LIWC, see Pennebaker et al., 2015; Wolf et al., 2008). It could, hence, be assumed that correct personality estimations, for instance, were mediated by meaning or style above the one-word level. Going back to Figure 1, if someone writes, "I have just finished my PhD," the conclusion from the semantic meaning of the sentence that this person is quite smart has a high intuitive probability (though it might be a lie after all). More precisely, a human would most probably build her/his judgement on the (optimistic) heuristic that people with a PhD are smart, but the search mechanism of LIWC would detect only very small parts of that meaning if any meaning at all.

7.3 Limitations

It should be noted that personality questionnaires can be affected by acquiescence and social desirability (e.g., Navarro-González, Lorenzo-Seva, & Vigil-Colet, 2016). The latter aspect could become particularly relevant in the context of mating and dating, as this could be especially related to impression management (Goffman, 1959), which might have played a crucial role in both of our studies. It can be assumed that it was in the natural interest of our participants to appear as desirable as possible. Considering this, it does not seem unlikely that in step one (when filling out, among others, the Big Five questionnaire) of each of the two studies, our participants already presented themselves as more socially desirable with respect to their personality than they actually were. During the speed dating sessions they should, of course, have presented themselves in a more desirable way, too. We therefore explain parts of the much higher Bayes factors of intelligence compared to the Big Five with the fact that an intelligence test as a measure is far harder to fake for reasons of impression management compared to a questionnaire scale that relies on mere self-description like a Big Five inventory (e.g., Birkeland, Manson, Kisamore, Brannick, & Smith, 2006; Furnham, 1990). Therefore, social desirability might have had a huge impact on our results and future research should consider how to control for it in dynamic settings. Additionally, we have a relatively low sample sizes despite having carried out two studies (Cohen, 1988) and despite the Bayesian approach the data is of course not immune to some bias in our samples. However, we did our best to gather as much data as possible through our laboratory resources and the pool of interested people in our speed dating sessions. In this context, it also needs to be discussed that in comparison with Study 1, relatively few participants who had filled in the online questionnaire of Study 2 actually came to the actual speed dating sessions. This had to do with a (for us) surprising difficulty of finding enough men and resulting problems in scheduling speed dating sessions. This might have led to some sort of self-selection bias in favor of participants that were eager to wait for a session. Of course, this might have had an impact on the generalizability of our data. Finally, when we compare our evidence with the results of studies that worked with more static cues like online user names (Lange et al., 2019), simply by comparing the effect sizes in our research at hand to other research, we see a tendency that humans might be better at using these static cues to assess personality. This might be related to our participants' higher mental effort caused by the fact that they had only limited time to "advertise" themselves to a potential mate. Therefore, our results are only partially comparable to static cmc settings.

7.4 Outlook and Conclusion

Despite the mentioned limiting factors, we are confident that our results can be generalized to a wide variety of text-based online dating applications as 85% of Tinder users, for example, are between 18 and 35 (Smith, 2020), which is very similar to the age of most participants in our samples. Furthermore, the use of Tinder also requires a lot of stamina for most users, because of the 210 million matches found for users every week, only 1.5 million dates actually take place, which is a total of less than 1%.

Having said that, we think that further research needs to be conducted to assess how humans perceive cmc as its applications are increasingly becoming a major part of human life (Finkel et al., 2012). Also, more and more non-verbal cues can be embedded in cmc (e.g., voice messages in WhatsApp, gifs, videos), which may have had an influence on personality ratings as well. As to the research at hand, personality and intelligence judgments must have resulted from the linguistic features of the chats, as all other cues were eliminated from the setting. Consequently, we assume that valid cues for personality assessments are still available within the chat logs – however, these may not be determined by LIWC or other word count oriented/quantitative text analysis tools. Hence, future research that goes beyond the possibilities of LIWC should try to identify such linguistic cues.

To conclude, we provided some evidence that people are able to make correct inferences, at least about the direction, of the personality and intelligence of potential mates in the dynamic setting of speed dating, although it is not entirely clear which cues they rely on. Future research needs to identify these cues.

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