The Expression of Personality in Virtual Worlds

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Abstract

To examine the expression of personality in virtual worlds (VWs), we tracked the behavioral and linguistic output of 76 students continuously over a six-week period in the VW *Second Life* (SL). Behavioral metrics in SL were consistent over time, but low stabilities were observed for linguistic metrics. To examine the ways in which personality manifested in SL, participant's Big Five scores were correlated with their virtual behavioral and linguistic metrics. For example, Conscientiousness was correlated with many metrics related to geographical movement, however, there was low overlap with findings from previous studies. We provide some reasons for this low concordance. Our study hints at the potential of leveraging VWs to understand not only the link between personality and behavior, but among other social and psychological phenomena as well.

The Expression of Personality in Virtual Worlds

Every morning, at exactly 7 o'clock, Stella treks to her farm to harvest and plant a new crop of peas, but in the popular FaceBook harvesting game *FarmVille*, she can do this without even breaking a sweat. And over in the virtual world *Second Life* where users create all of the world's content, Marcus is wondering whether his new mohawk hairdo would send the wrong message at the academic panel he is attending or whether it would be considered stylish in the context of *Second Life*. As virtual worlds (VWs) become mainstream, a critical psychological issue is whether and how personality manifests itself in VWs.

The Expression of Personality

Research in person perception has consistently shown that judgments of personality at zero acquaintance hold some degree of validity. This has been shown to be true for face-to-face encounters (Kenny, Horner, Kashy, & Chu, 1992), as well as judgments based solely on observations of an individual's bedroom or office (Gosling, Ko, Mannarelli, & Morris, 2002) or their music preferences (Rentfrow & Gosling, 2006).

Similar research has also extended to computer-mediated communication (CMC). In particular, past findings have shown that somewhat accurate personality impressions can be formed based on an individual's personal website (Marcus, Machilek, & Schutz, 2006; Vazire & Gosling, 2004), FaceBook profile (Back, et al., 2010), email content (Gill, Oberlander, & Austin, 2006), and even an individual's email address (Back, Schukle, & Egloff, 2008).

In exploring different methods of studying personality manifestation, some researchers (Mehl, Gosling, & Pennebaker, 2006) have illustrated the value of using natural observations to study personality as it manifests in everyday life. Collecting observations of natural behavior,

however, is a daunting task where the tedium of continuous observations has only recently been offset by modern technology.

Unobtrusive Observations in Virtual Environments

Virtual Worlds provide unique affordances for studying the link between personality and behavior. For the purposes of this paper, we define VWs as graphical environments that enable geographically-distant individuals to interact via graphical avatars (i.e., digital representations of users). These environments are no longer academic prototypes, but have become mainstream interaction platforms. For example, the online game *World of Warcraft* has over 11 million active subscribers world-wide (White, 2008). *Second Life* is another example of a VW, and is unique in that users in *Second Life* create almost all the content (i.e., buildings, cars, dresses, hair styles, dance animations) in the world using scripting and modeling tools. This is in contrast to most online games where players can only use and interact with the content created by game developers.

There are three unique affordances of VWs with regard to natural observations of behavior. First, VWs are already instrumented with high-precision sensors. The computer systems running VWs already track the movement and behavior of every avatar to make interaction possible. Second, these high-precision sensors can track behaviors continuously and longitudinally. And finally, all these observations can be performed unobtrusively, thereby eliminating the observer effect (Webb, Campbell, Schwartz, & Sechrest, 1966).

Stability of Behavioral and Linguistic Metrics in Virtual Worlds

Given that almost all studies of person perception in online environments have employed static or snapshot observations, such as personal websites (Marcus, et al., 2006), the stability of behavior and linguistic output in digital environments and its relation to personality

manifestation is understudied. Important clues can be inferred from other studies however. For example, written language use in diaries, class assignments, and professional journal abstracts has been shown to be quite reliable over weeks and even years (Pennebaker & King, 1999). And in a study of everyday conversational language collected via automated voice recorders (Mehl & Pennebaker, 2003) across two-day periods separated by four weeks, linguistic measures were also observed to be highly consistent. Thus, these two studies show that both spoken and written language appears to be quite stable over time in physical contexts.

In one of the few longitudinal studies of behavior in virtual environments, it was found that behavioral changes over time do occur as users acclimate to interacting via digital avatars, but that these changes occurred across all users (Bailenson & Yee, 2006); however, personality factors were not explored in that study. If we assume that this pattern generalizes to most VWs, then it implies that rank-order stability may be high even though absolute stability is low--i.e., over time, VW users may all explore less, but some users will always tend to explore more than other users. Consequently we seek to examine the stabilities of behavioral and linguistic output in VWs.

RQ1a: Are behavioral and linguistic measures in virtual worlds stable over time in absolute terms?

RQ1b: Are behavioral and linguistic measures in virtual worlds stable over time in relative terms?

Manifestation of Personality in Virtual Worlds

Research in person perception has documented the ways personality manifests itself in a wide variety of environments. Here, we will first consider past studies in behavioral correlates and then linguistic correlates of personality. In an early study of how personality manifested in

normal face-to-face conversations (Funder & Sneed, 1993), coders rated participants in a social interaction using 64 behavioral categories. Acquaintances of participants then rated each participant using a Big5 personality inventory. Many significant correlations were observed between the personality ratings and the coded behaviors, most of which aligned closely with trait definitions of the personality factors. For example, Extraverted individuals spoke louder, with more enthusiasm and energy, and were more expressive. Agreeable individuals expressed sympathy, seemed to enjoy the interaction with their partner, and expressed interest in what their partner said.

In another study, researchers explored the manifestation of personality in personal spaces (Gosling, et al., 2002). Thus, instead of observing behaviors directly, personal spaces hold identity claims (e.g., a poster of Nietzsche) and behavioral residues (e.g., a withered house plant) that reflect personality more indirectly. Nevertheless, researchers found significant correlations between coded personal space attributes and self-report personality ratings of individuals. In their study of bedrooms, it was found, for example, that individuals who scored high on Openness to Experience had more varied books and magazines. As another example, Conscientious individuals had more well-lit, neat, and well-organized bedrooms.

These two studies were selected to illustrate how direct and indirect behavioral correlates of personality have been observed in the past. It is unclear, however, how these might translate into virtual worlds. For example, while individuals are able to interact in virtual worlds, many virtual worlds do not have user-controlled facial or hand gestures. And it is unclear how varied book collections translate into virtual worlds where people don't read virtual books. On the other hand, as we mentioned above, there are a plethora of behavioral metrics that virtual worlds provide, such as geographical movement that may nevertheless be significant personality cues.

Unlike behavioral correlates, linguistic correlates of personality may translate more directly into virtual worlds. To provide an overview of findings in this area, we describe four studies that have all used the Linguistic Word Count and Inquiry software (LIWC; Pennebaker, Booth, & Francis, 2007) to examine linguistic correlates of personality. LIWC is a dictionary-based word count tool that counts the ratio of words in 70 linguistic categories. For example, the category "positive emotion" contains the words: happy, cheerful, joy, etc. The four selected studies span the past decade and examine different linguistic content: personal writing profiles (Pennebaker & King, 1999), self-narratives (Hirsh & Peterson, 2009), everyday conversations (Mehl, et al., 2006), and blog content (Yarkoni, in press).

Table 1

A summary of previous linguistic correlates with personality factors

Personality Factor	Positive Correlates	Negative Correlates
Emotional Stability	Articles	Anger, Anxiety, Negative Emotions, First Person Singular
Extraversion	Social Processes, Positive Emotions	
Openness to Experience	Articles, Exclusives	First Person Singular, Present Tense, Past Tense, Social Processes
Agreeableness	First Person Singular, Inclusives, Family, Positive Emotions	Articles, Anger, Negative Emotions
Conscientiousness	Achievement	Causation, Exclusives, Anger, Negations, Negative Emotions

To provide a concise and coherent summary of the findings (oftentimes with hundreds of comparisons) without being bogged down by idiosyncratic differences, we will summarize only correlates that were found to be significant in at least two studies (see Table 1). Of note, most linguistic correlates mirror trait definitions. For example, Emotional Stability is negatively

correlated with negative emotions, and Agreeableness is positively correlated with social involvement and positive emotions. On the other hand, grammatical features such as articles and first person singulars also made frequent appearances (both were significant correlates in three out of the five personality factors) although their connection with personality is less obvious.

Thus, in the present study, we were interested in the following research question:

RQ2: What behavioral and linguistic correlates of personality in virtual worlds?

Method

Participants

Seventy-six participants (25 female) consisting of undergraduate and masters students participated in the study as part of a class that was largely designed around their participation in *Second Life* (SL). None of the participants had previous experience with SL. Over the course of the six-week study the average number of hours spent in SL was 36.03 (SD = 5.27). The mean age of the participants was 21.07 (SD = 3.68).

Procedures

Prior to the start of the experiment, all participants were required to attend a one-hour tutorial in which they were taught the basics of SL. Upon creating their new avatar, they visited the experimenters in SL to receive two items. First, each participant was given one thousand Linden dollars (L$1000) to use as they wanted. Then, a *Sender* object was transferred to the participant, and the experimenter confirmed that it was attached to the avatar. The *Sender* was developed using SL's scripting language (LSL). When attached to the avatar, the tool gathered data on movement, action, and chat every 10 seconds, and then transmitted the information to a database. The details of the script used to create the *Sender* are described in previous work (Yee & Bailenson, 2008). Participant were asked to spend at least six hours each week in SL, and

their behaviors in SL were logged for six weeks. Participants did not have access to the database where their logged data was stored.

Measures

Personality Measures. A 50-item scale measuring the Big-Five Factor structure was drawn from the International Personality Item Pool (Goldberg, 1999). Participants rated themselves on the inventory items using a scale that ranged from 1 (*Very Inaccurate*) to 5 (*Very Accurate*). The alpha reliabilities for Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Openness to Experience were .90, .70, .72, .85, and .78 respectively.

Virtual Behavior Metrics. The *Sender* collected longitudinal data of participants' behaviors over the six week period. These behaviors included their current stance (e.g., walking, flying, sitting), their Cartesian coordinate in the world, the number of other avatars within a 20m radius, how often they logged on SL, and whether they were typing. The world of SL is divided into many different square zones with touching edges. SL users are thus always located in one particular zone and this was also recorded by the *Sender*. Of note, it is also possible for SL users to fly as a form of locomotion. From these raw data points, we generated 17 behavioral metrics and calculated the means for these metrics for each week. In Table 2, we show the averaged weekly metrics over the 6 weeks.

Linguistic Measures. The *Sender* also collected the frequency that participants used the in-world text chat and the content of their text messages. These text messages were analyzed using the word-based language analysis program Linguistic Inquiry and Word Count (LIWC; Pennebaker, et al., 2007). LIWC outputs the ratio of total words that fall into each of the 70 categories (e.g., first-person singular pronouns). Past research in linguistic analysis of personality projection in everyday life has identified a set of 23 variables of interest. For the current study,

Table 2

Description of the behavioral metrics, along with their respective means, standard deviations, averaged pair-wise correlations over the six weeks, and the F-value from the repeated measures ANOVA over the six weeks.

Variable	Description	Mean	SD	r	F
Fly	Ratio of time flying	.07	.11	.40*	5.38*
Walk	Ratio of time walking	.06	.06	.26*	9.45*
Run	Ratio of time running	.03	.08	.33*	5.84*
Sit	Ratio of time sitting	.40	.30	.49*	17.02*
Type	Ratio of time typing	.02	.02	.30*	4.21*
Teleports	Number of teleports	15.87	12.66	.37*	30.91*
Favorite Zone	Ratio of time spent in the participant's most visited zone	.55	.28	.32*	29.74*
Unique Zones	Number of unique zones visited	15.03	13.59	.41*	26.76*
Logins	Number of times the participant logged in	11.51	8.75	.26*	11.78*
Login Time	Average time the participant spent in SL each unique login (in minutes)	49.11	56.11	.30*	10.77*
Total in Radius	Average number of other avatars in the participant's 20m radius	4.19	3.77	.41*	3.10*
Max in Radius	The maximum number of other avatars in the participant's 20m radius	13.46	4.62	.22	3.83*
Zero in Radius	Ratio of total time with no other avatar within a 20m radius	0.35	0.29	.36*	1.85
Total Distance	Total distance traveled (in SL meters)	6224.71	6639.80	.39*	15.82*
Walked Distance	Distance walked (in SL meters)	3777.53	4522.50	.34*	6.46*
Flown Distance	Distance flown (in SL meters)	2447.18	3652.28	.42*	14.49*
Zone Crossings	Number of zone crossings made	23.10	22.28	.41*	20.73*

Note. * $p < .05$

we used these variables for the analysis, except for two variables associated with spoken language but not typed chat (i.e., nonfluencies such as "ummm" and filler words such as "yaknow", "Imean"). We also included "Future Tense", as both "Present Tense" and "Past Tense" were included as variables of interest in the past. Finally, we added one chat frequency variable collected by the *Sender*--a count of the number of chat lines (which is different from the count of all words). Thus, we included 23 linguistic variables in the analysis. In Table 3, we show the

descriptions, and the averaged weekly means, and standard deviations for these linguistic variables over the 6 weeks of the study. Note that LIWC outputs ratios from 0-100 (i.e., 50 is equal to 50%) and we follow this format in showing the means in the table.

Table 3

Description of the linguistic metrics, along with their respective means, standard deviations, averaged pair-wise correlations over the six weeks, and the F-value from the repeated measures ANOVA over the six weeks.

Variable	Description	Mean	SD	r	F
Chat Lines	Number of chat lines	65.50	62.70	.34*	.56
Word Count	A count of all the words in the text messages sent	260.12	215.84	.25*	7.13*
Words w/ More Than 6 Letters	A count of all words with more than 6 letters	7.18	3.99	.15	.24
First-person singular pronouns	I, me, my	5.15	2.19	.12	3.53*
First-person plural pronouns	We, us, our	.36	.33	.07	1.82
Total second-person pronouns	You, your	3.06	2.23	.32*	.99
Total third-person pronouns	She, him, their	.48	.44	.06	1.12
Negations	No, not, never	1.52	.85	.05	.64
Articles	A, an, the	2.71	1.35	.15	2.06
Prepositions	To, with, above	5.95	2.60	.24*	2.93*
Swear Words	Damn, bastard	.55	.85	.20	.56
Positive Emotions	Happy, good	6.54	3.23	.13	.88
Negative Emotions	Hate, ugly	1.66	1.58	.12	.86
Causation	Because, effect	1.69	1.09	.04	1.35
Insight	Realize, know	1.27	.75	.14	3.26*
Discrepancy	Would, should	1.04	.74	.08	1.06
Tentative	Perhaps, maybe	1.92	1.18	.13	3.35*
Social Processes	Friend, talk	11.86	6.28	.05	1.73
Past Tense	Was, went	1.80	1.15	.17	.60
Present Tense	Is, go	11.71	4.44	.16	6.95*
Future Tense	Will be, will go	.56	.46	.13	1.63
Inclusive	With, and	1.49	.76	.07	2.68*
Exclusive	Except, but	1.57	.85	.11	1.55

Note. Means are weekly averages. Thus, the overall six-week average number of chat lines produced is six times what is listed as the weekly mean. * $p < .05$

Results

Stability of Behavioral and Linguistic Metrics in VWs Over Time

To examine the absolute stability of the VW metrics over time, we conducted repeated-measure ANOVAs for each measure over the six-week period. The resulting F-values and corresponding significance levels are shown in Tables 2 and 3. Among the behavioral metrics, 16 of the 17 metrics were significantly different over time. Among the linguistic metrics, 7 of the 23 were significantly different over time.

To examine the rank-order stability of the VW metrics over time, we calculated the average of all pair-wise correlations for each variable over the six weeks. The resulting average correlation coefficient is also shown in Table 2 and 3. Among the behavior metrics, 16 of the 17 correlation coefficients were significant, and the overall average correlation r was .35. Among the linguistic metrics, 4 of the 23 correlation coefficients were significant, with an overall average correlation r of .14.

Figure 1. Average unique zones visited by week with 95% CI error bars.
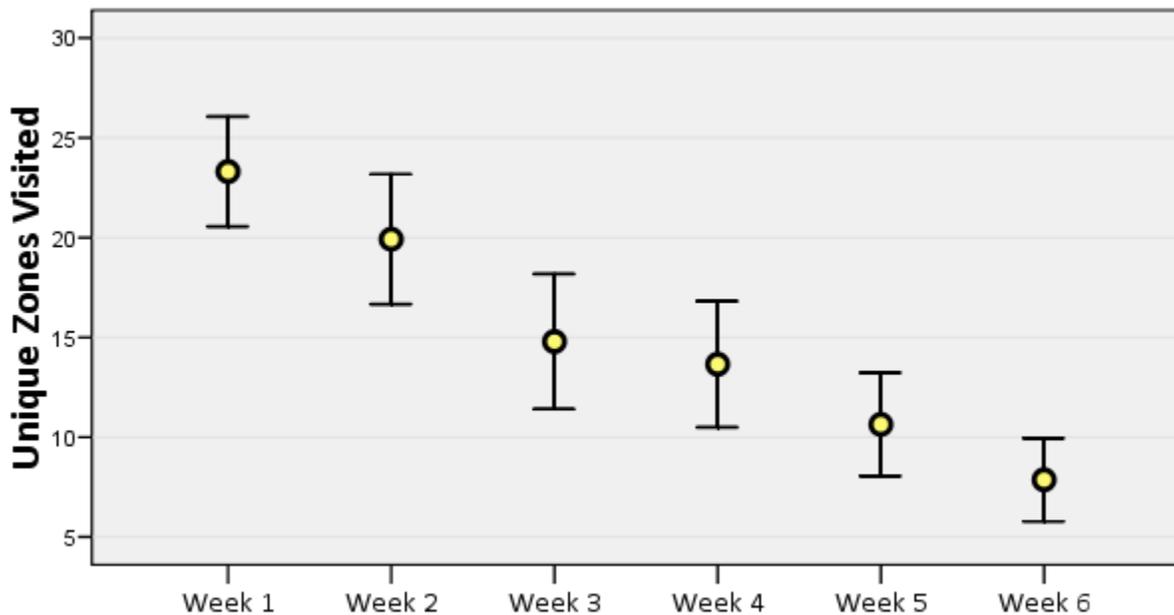
This suggests that behavioral metrics in SL have high rank-order stability even though the absolute stability is low. As an illustration of these changes over time, the plot of visits to unique zones (i.e., the number of different areas of the SL world that a user walked through) over the six-week period shows a significant linear contrast, $F[1, 74] = 117.48$, $p < .001$ (see Figure 1). While the repeated-measure ANOVAs suggest that virtual behavioral metrics change over time, the averaged pair-wise correlations suggest that they nevertheless capture relative individual differences beneath these global trends.

On the other hand, the analyses show that linguistic content in SL is neither very stable in absolute or relative terms. Nevertheless, given that we collected data over a six-week period, there is still the potential that the mild stabilities in linguistic output aggregated over time may yield some markers of personality expression.

Markers of Personality in VWs

Given the increased risk of experiment-wise error in large correlation tables with 39 variables against the Big Five Factors, we used an analytic method developed by Sherman and Funder (2009) to address this specific issue. The method employs a Monte Carlo simulation of repeatedly randomized data within each participant. Thus, the method preserves the statistical properties of the data gathered. The method conducts 1000 of these randomized data sets and tabulates the number of observed significant correlations (at alpha of .05). The probability of the actual number of significant correlations is then calculated based on where it lies on the distribution of the 1000 randomizations. In our case, using an alpha of .05, we had 26 observed significant correlations where only 10.68 would be expected by chance based on the simulations. According to this Monte Carlo method, the probability of this number of observed correlations is $p = .02$. This provides assurance that the observed correlations, as a set, are non-random. We

present the significant correlations in Table 4 and compare them with our summary of previous

findings mentioned in the introduction.

Table 4

Significant correlations between personality factors and the behavioral and linguistic metrics.

	Big5A	Big5C	Big5E	Big5ES	Big5O
Behavioral Measures					
Walk	0.19	**0.33**	0.13	0.04	**0.23**
Teleports	0.18	**0.29**	**0.28**	-0.11	0.08
Favorite Zone	-0.07	**-0.26**	-0.15	0.10	-0.18
Unique Zones	0.17	**0.26**	0.17	-0.02	-0.01
Logins	0.07	0.15	0.07	**-0.23**	0.00
Login Time	0.08	-0.05	-0.16	**0.28**	0.10
Zero in Radius	0.13	**0.26**	0.09	0.05	0.15
Total Distance	**0.25**	0.16	0.06	-0.04	0.00
Walked Distance	**0.24**	**0.23**	0.11	-0.02	0.03
Zone Crossings	0.19	**0.24**	0.14	-0.03	-0.03
Linguistic Measures					
Words w/ More Than 6 Letters	0.15	**0.34**	**0.24**	0.11	0.05
First Person Singular	0.08	-0.07	**0.22**	**-0.23**	0.04
Total Second Person Pronouns	0.04	0.21	-0.06	**-0.31**	-0.10
Swear Words	-0.08	-0.11	**-0.29**	-0.06	-0.09
Causation	0.04	0.03	0.00	**-0.24**	-0.01
Discrepancy	-0.09	-0.09	-0.14	**-0.25**	-0.14
Tentative	-0.14	**0.25**	0.18	-0.07	-0.08
Present Tense	-0.12	0.09	0.13	**-0.24**	0.02
Future Tense	0.19	0.04	0.09	**-0.30**	0.02
Inclusive	-0.03	0.04	0.12	**-0.26**	0.05
Exclusive	-0.06	-0.01	**0.26**	-0.06	-0.05

Note. Bolded coefficients are $p < .05$.

Here we briefly highlight some clusters of related correlates in Table 4. Conscientiousness was

correlated with many variables related to geographical movement, such as distance walked and

number of unique zones visited. Emotional Stability was related to log-in patterns--participants

low on Emotional Stability logged in more often but with shorter durations. Participants low on Emotional Stability were also more likely to reduce their use of common linguistic features, such as pronouns and tense markers. On the other hand, it is more difficult to make sense of the correlates for the other three personality factors; there was only one significant correlate for Openness and two correlates for Agreeableness. The correlates for Extraversion are also difficult to interpret as a whole.

Discussion

Our study illustrates that the affordances of VWs can be leveraged to collect large amounts of detailed longitudinal behavioral and linguistic metrics from these environments unobtrusively. Overall, while our findings suggest that personality is expressed in virtual worlds via both behavioral and linguistic correlates, the specific correlations we found did not match those identified in previous studies nor were they easily interpretable for the most part.

Similar to the pattern observed in a longitudinal study of interactions in a virtual environment (Bailenson & Yee, 2006), we found that while absolute stability was low in terms of behavioral metrics in VWs, the rank-order stability was robust. On the other hand, the stability of linguistic metrics in VWs was low. This is in contrast to a study of linguistic stability in everyday life (Mehl & Pennebaker, 2003). One potential explanation is that the varied settings (i.e., teleporting from a poetry reading to a disco party) in SL introduced a high amount of noise into the linguistic metrics. In contrast, linguistic interactions in everyday life are often part of a routine and familiar to the individual. While it is not clear what impacted the stability of linguistic metrics in our study, some of the aggregate linguistic measures over the six-week period did correlate well with personality factors, so it appears that markers of personality

expression can be derived from linguistic metrics in VWs by aggregating over a large period of time.

Significant behavioral and linguistic correlates were found for all the Big Five Factors, however, our findings do not match up well with findings from the previous studies summarized in the introduction. In comparing our findings with the summarized findings in Table 1, we find only one match between the current data set and previous findings, the correlation between common linguistic features and emotional stability. It is troubling that the correlations from the current study did not replicate those found in much of the previous work. On the other hand, none of the findings in this study directly contradict (i.e., show a significant opposite signed correlation) those in Table 1.

After observing the low concordance between our linguistic correlates and those observed in previous studies, we skimmed through the actual logged chats and noticed several unique features of chat in SL. Our first clue that chat on SL was very different from the comparison linguistic samples in previous studies was the observation from Table 3 that the average chat line only contained about four words. Perusal of the actual chat logs also revealed that SL users often employed abbreviations such as "U" for "you" or "rly" for "really". They also employed many common internet acronyms such as "lol" for "laughing out loud" or emoticons as "<3" for the heart symbol. We also observed frequent typos, sentence fragments, and pronoun drops (e.g., "busy now" instead of "I'm busy now"). These unique linguistic features of chat in SL likely contributed to both the low stability of the linguistic measures as well as their non-concordance with findings from previous studies. Indeed, scholars have noted that instant messaging has its own lexicon, grammar, and usage conditions and is distinct from written prose and normal speech (Crystal, 2001; Ling & Baron, 2007; Tagliamonte & Denis, 2008; Walther,

Gay, & Hancock, 2005). Our findings highlight the fact that while many Web 2.0 systems provide a wealth of linguistic data, it is important for researchers to develop linguistic tools that can take into account the unique linguistic aspects of communication in these novel environments.

Despite the limitation of the chat data, the current data is exciting because it adds the use of behavioral and nonverbal data as a tool to examine personality. As Table 4 demonstrates, a number of features based on locomotion and geography are significant correlates of personality, especially conscientiousness. While the linguistic data may be limited based on the specific chat setup in Second Life, the richness of the behavioral data provide unique insights.

There were several other limitations to the study. First and foremost, our study focused on only one VW. While some personality cues may appear in other VWs, it is at present not clear how many of our findings generalize to other VWs. Secondly, only undergraduate students were included in the study sample and this too may limit its generalizability. And finally, in hindsight, the behavioral metrics we logged largely centered on variations of geographical movement and in turn may have constrained the manifestation of personality in VWs we could identify. For example, we tracked movement through different zones but had no good way of coding for the content of those zones, or the context of social gatherings. The affordances of different VWs or creating tools to extract more contextual data may reveal other behavioral correlates.

Nevertheless, our findings do show that there are significant manifestations of personality in VWs. The behavioral correlates suggest that Conscientiousness is related to geographical movement in VWs and that Emotional Stability is related to login patterns. Overall, we believe that the current study presents a first step in understanding personality expression in the novel domain of virtual worlds. As Mehl and his colleagues noted (2006), capturing people's

interactions in the physical world reveals what people spontaneously do, what they avoid, and their idiosyncrasies. The value in natural observations lies in its ability to "document personality right where it occurs" (pg. 875). While natural observations of virtual behavior may seem ironic at first glance, it is important to remember that much of our daily lives now take place in virtual places. For example, the average online gamer spends more than 20 hours a week in their game avatars (Williams, Yee, & Caplan, 2008; Yee, 2006). More importantly, the viability of longitudinal behavioral tracking leveraging VWs as a methodology extends well beyond the domain of personality psychology. Indeed, it is not difficult to imagine using a similar methodology to examine the emergence or stability of social norms, leadership, or stereotypes. In sum, virtual worlds offer both new methods and new contexts to understand the links between psychological factors and social phenomena.

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