Mouse movements reflect personality traits and task attentiveness in online experiments

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Mouse movements reflect personality traits and task attentiveness in online experiments

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Abstract

In this rapidly digitizing world, it is becoming ever more important to understand people's online behaviors in both scientific and consumer research settings. A cost-effective way to gain a deeper understanding of these behaviors is to examine mouse movement patterns. This research explores the feasibility of inferring personality traits from these mouse movement features (i.e., pauses, fixations, cursor speed, clicks) on a simple image choice task. We compare the results of standard univariate (OLS regression, bivariate correlations) and three forms of multivariate partial least squares (PLS) analyses. This work also examines whether mouse movements can predict task attentiveness, and how these might be related to personality traits. Results of the PLS analyses showed significant associations between a linear combination of personality traits (high Conscientiousness, Agreeableness, and Openness, and low Neuroticism) and several mouse movements associated with slower, more deliberate responding (less unnecessary clicks, more fixations). Additionally, several click-related mouse features were associated with attentiveness to the task. Importantly, as the image choice task itself is not intended to assess personality in any way, our results validate the feasibility of using mouse movements to infer internal traits across experimental contexts, particularly when examined using multivariate analyses and a multiverse approach.

1. Introduction

The rapid development of digital technology has led people to spend an increasing amount of time online. As people navigate through different web applications, they leave digital traces behind. One of these implicit traces is mouse movements. Regardless of the motivation, people use their mouse to guide and shape their online experiences. As humans naturally infer internal states from physical motion cues (Koppensteiner, 2013), a similar process can be used to infer an individual's internal states based on online behavioral cues. This research attempts to examine a related topic on the relation between an individual's online behaviors and personality traits. More specifically, the research question of interest is 'Are mouse movement patterns exhibited in a choice-making task reflective of a person's internal states and traits?'

Mouse cursor movements are a cost-effective measurement of individuals' behaviors. Mouse trajectories have been used in previous research to track attention in computer interactions (Rodden et al., 2008) and measure website engagement (Arapakis & Leiva, 2016). It has also been shown that mouse movements are significantly correlated with individuals' attitudes. In the context of evaluating implicit bias, researchers have examined the time and trajectory from one location on screen to another to evaluate hesitancy or "corrections" to initial decisions (Hehman, Stolier, & Freeman, 2014; Freeman, 2018; Stolier & Freeman, 2016). Work by Katerina et al. (2014) showed that mouse hover time and movement patterns can be used to predict an individual's self-efficacy and risk-perception. The same researchers found that a person's attitude toward a web-based tool, such as perceived usefulness or perceived ease of use of that tool, can also be inferred from their mouse movements (Katerina & Nicolaos, 2018). This research highlights the potential of mouse movement to effectively predict internal states and attributes. In this study, we specifically explore the relationship between participants' mouse movement patterns and two types of individual attributes — attentiveness to the task at hand, measured by the deviation of individual responses from random responding, and personality, as measured by the Big Five Inventory.

The Big Five Inventory (BFI) is a self-report survey designed to measure one's personality across five dimensions: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (John & Srivastava, 1999). Each of these five dimensions consists of several sub-traits. For example, Neuroticism consists of traits such as anxiety, depression, self-consciousness, and vulnerability. Researchers have shown that personality traits are related to a wide range of behaviors. Of key relevance to the current work, it has been found that one's behaviors online are reflective of a person's off-line personality (Orchard & Fullwood, 2010) outside of the computer screen. Importantly, one's personality can be used to predict Internet addiction (Sariyska et al, 2014) and therefore it might be useful to uncover an individual's personality characteristics from mouse movements to know if internet users may become addicted.

Combining personality traits with mouse movements, studies have found that extroverts tend to exhibit higher levels of motor activity (mouse clicking) at a higher frequency in a given task (Brebner, 1983; Khan et al., 2008), and that keystrokes and mouse clicking behaviors are significantly correlated with Big Five personality traits (Khan et al., 2008). In particular, it was found by Khan and colleagues (2008) that average number of mouse clicks was positively correlated with a sub-trait of Conscientiousness and negatively correlated with a sub-trait of Neuroticism. However, both personality traits and mouse movements can show high levels of intercorrelation, and it is therefore likely that multivariate methods which identify a combination of mouse features and personality traits would create a better understanding of this link.

Across academic- and consumer-focused research, participants' inattentiveness in online research can significantly damage the validity of a study. Different attempts have been made to filter out non-complaint responses such as setting a higher standard to select participants with good records, embedding attention check questions within a survey, or evaluating personality inventories and flagging abnormalities (Barends & de Vries, 2019). In addition to these methods, it has been found in previous research that in certain tasks involving image recognition, mouse-click attention tracking can provide highly valid results that are more consistent than eye movement attention tracking (Egner et al, 2018). This study proposes mouse tracking as another effective approach for detecting general attentiveness.

Importantly, (in)attentiveness during online research can also be reflective of a participant's personality (i.e., those higher on the BFI trait of conscientiousness tend to show greater compliance in experiments; Meade & Pappalardo, 2013, Berry et al., 2019). Therefore, instead of assuming independence between mouse movement features, attentiveness and personality, we conduct multivariate partial least squares (PLS) analysis to further explore the underlying relationships between these features. Additionally, we adopt a multiverse analytic approach (Steegen et al., 2016), comparing the results of PLS analysis with and without demographic factors and with and without our task attentiveness measure to evaluate the constraints of the relationship based on the variables considered.

Overall, the results of the current work demonstrate that mouse movements can indeed be used to predict individuals' personalities in an online task. We find that individuals high on Conscientiousness, Agreeableness, and Openness and low on

Neuroticism show patterns of mouse movements related to less unnecessary clicking and slower, more deliberate responding, and that click-based mouse features can predict inattentiveness in an online experiment. Perhaps most notably, these results come from mouse movement features in a simple image-rating task that was not designed to predict personality traits, demonstrating the potential for this method to be used across a variety of experimental contexts.

2. Method

2.1. Data Sources

Raw data used in this research combines data collected from two different studies at the University of Chicago. Both studies recruited participants from Amazon Mechanical Turk (AMT). All participants provided informed consent before continuing to the study procedures. In each study, participants were asked to complete an image-rating task, which involves making choices based on given judgement (e.g., pick the 4 images that you like the most). Each participant completed multiple trials of the same task.

After completing the image-rating task, participants were asked to fill out the Big Five Inventory (BFI) questionnaire, which includes 44 items that measure an individual's personality across five dimensions (John & Srivastava, 1999). A normalized personality score for each dimension was calculated and stored for further analysis. Participant's basic demographic information, such as gender and age, were also collected at the end of the task.

We used the JavaScript library jQuery to record participants' mouse movements. A record is created whenever a movement occurs. A continuous cursor movement is captured at around 60 Hz, or every 17 milliseconds. However, the exact frequency depends on the type of mouse or touchpad used. Four variables were recorded for each mouse movement entry: 1) timestamp in milliseconds, 2) the cursor's x coordinate in pixels, 3) the cursor's y coordinate in pixels, and 4) a dummy-coded variable for click (1 if the participant clicked in the recorded position, and 0 if the participant did not).

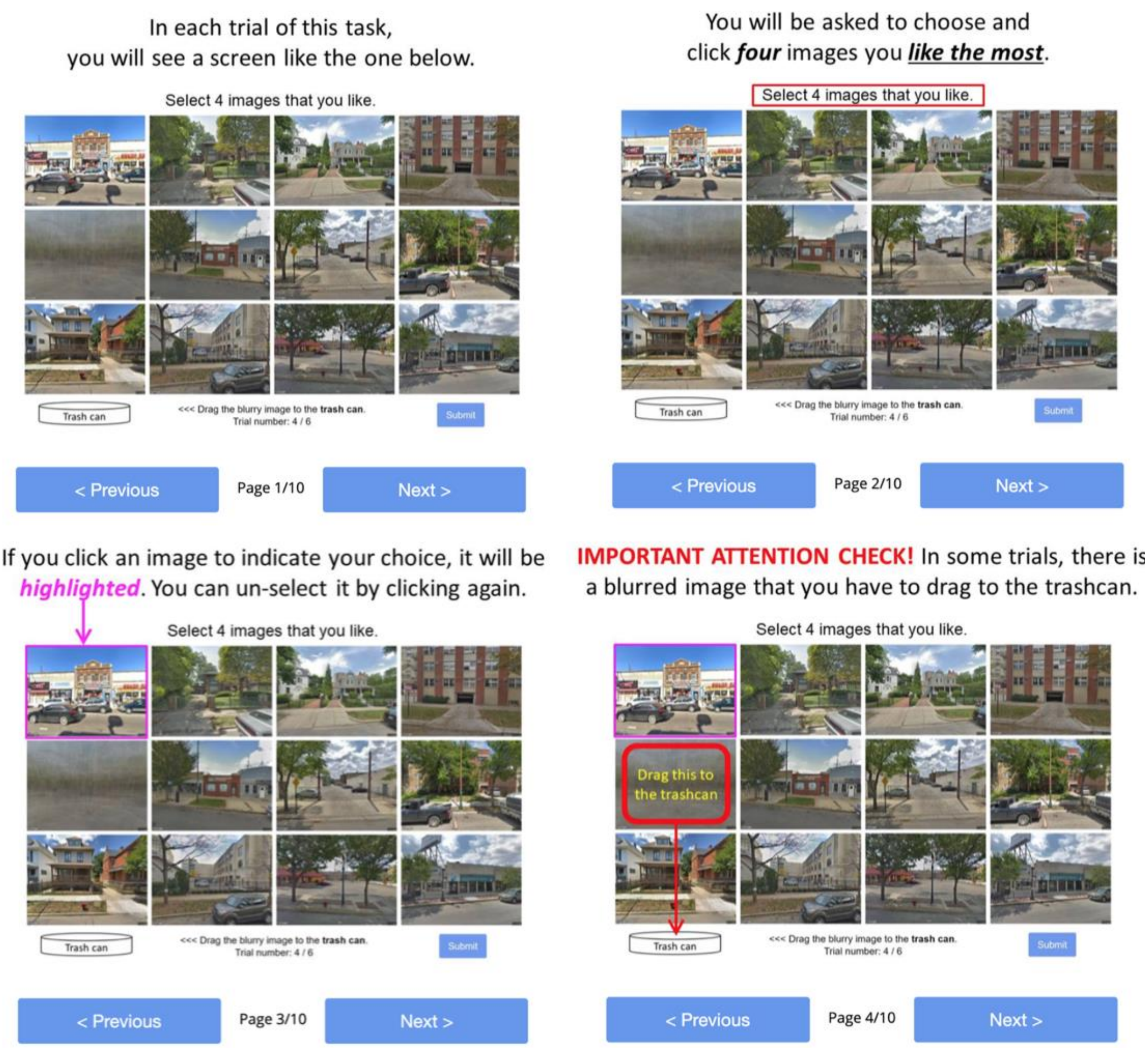
2.2. Participants

Participants were recruited using CloudResearch (https://www.cloudresearch.com/; Litman et al., 2017). After removing null values and invalid trials, the final cleaned data include 791 participants. Among them, 483 self-identified as *Male*, 303 self-identified as *Female*, and 5 self-identified as *Other*. Participants had a mean age of 38.8 years, with a standard deviation of 10.8 years.

2.3. Image-Rating Task

Data for this research come from a set of image rating tasks. Across all tasks, in each trial, participants were asked to look at 12 photos of streets taken at different angles and pick four images based on how high they were on a given attribute. A demo of the image rating task is available at: https://kywch.github.io/ImageRatingStudy/multi-image-rating-demo.html. For example, in one iteration, participants were asked to choose the four images they liked the most, and in a second iteration, they chose the four images they liked the least. In other versions, participants were asked to choose the four images highest on a given perceptual feature, such as perceived walkability, orderliness, complexity, etc. **Figure 1** shows the first four instruction pages shown to participants in the image-rating task. The instruction on the second page would differ based on the specific study conducted. To ensure the data were of sufficiently high quality, attention check questions were randomly distributed in multiple trials of the task to ensure data quality. During these trials, participants needed to drag a corrupted image into a trash can located in the bottom-left corner of the screen. Participants' sessions would be terminated if they failed to pass the attention checks twice.

Fig. 1: Instruction pages shown to participants during the image-rating task



2.4. Big Five Personality Inventory

The Big Five Inventory measures personality from five different dimensions: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Each dimension is composed of 6 sub-dimensions or traits. For example, Agreeableness measures trust, straightforwardness, altruism, compliance, modesty, and sympathy (John & Srivastava, 1999). The questionnaire is based on a five-point Likert Scale. Participants were asked to evaluate if a statement applies to themselves and choose from a 1 (= Strong Disagree) to 5 (= Strong Agree) scale. Their responses were normalized by summing responses then dividing by the number of questions for further analysis.

2.5. Mouse Feature Extraction

Code for extraction of mouse features can be accessed at:

https://github.com/tianyueniu/mouse_movement_personality

(i) Time-related features

Time-related features in this study refer to pauses and fixations. In this study, a long pause is defined as cursor inactivity for longer than 4 seconds (based on Katerina & Nicolaos, 2018), whereas a fixation is defined as micro-movements within 25 pixels that lasted for more than 250 milliseconds (based on Dalmaijer et al. 2014). The following features were extracted from raw mouse movement data.

total_pause_cnt: total count of long pauses across all trials.

avg_fixation_dur: average duration per fixation across trials.

avg_agg_fixation_dur: average total fixation time per trial.

avg_fixation_cnt: average number of fixations detected per trial.

(ii) Activity-related features

Activity-related features in this study include distance, time, and speed. The following features are extracted from raw mouse movement data.

avg_euc_dist : average Euclidean distance travelled in pixels per trial.

avg_euc_speed : average speed from pixel to pixel measured in milliseconds.

avg_completion_time: average trial completion time in milliseconds per trial.

(iii) Click-related features

To complete the tasks in this study, participants would have to click 5 times in normal trials (4 selection clicks and 1 click on the 'continue' button to move on to the next task), or 6 times in attention check trials (4 selection clicks, 1 drag click, and 1 'continue' button click). If a participant clicked for more times than necessary in a trial, we named the extra clicks as 'reclick'. The following clicks-related features are extracted from mouse movement data.

avg_click_att: average clicks made in attention trials.

reclick_percent_att: the percent of attention trials in which participants clicked for more times than necessary.

avg_click_norm: average clicks made in normal trials.

reclick_percent_norm: the percent of normal trials in which participants clicked for more times than necessary.

(iv) Inattentive Responding

Lastly, in this study, attentive responding is measured as the deviation from random responding. This calculation of random responding was based on whether a given participant's choices can or cannot predict the averaged choice probability across the whole group. To this end, Receiver Operator Characteristic (ROC) curves were calculated for an individual's decision (click or not) about each image relative to the group's average decision (highly clicked or not) about each image. That is, for any given image, if a participant chooses that image (click is 1) and the group average for that image is also very high (image is often chosen and therefore, the average value is close to 1), and vice versa, that participant's choice is highly predictive of the group's choice in a leave-one-out procedure. The Area Under the Curve (AUC) of this analysis reflects how similar the participant's responses are to the group's average responses across all images. If the clicks of an individual are highly predictive of the rest of the group, the AUC will be close to 1. In contrast, if the individual's choices are extremely different from the group's (i.e. intentional opposite responding), the AUC will be close to 0. An individual responding at random would have an AUC close to 0.5. This measure is stored as *Area_Under_Curve* in our data. We then calculated an *Abs_Area_Under_Curve*, which is equal to the absolute value of *Area_Under_Curve* - 0.5, to capture a participant's deviation from random responding, which is used as our final measure for attentiveness in our study.

2.6. Data Analysis Method

Eleven features were extracted from raw mouse tracking data as described in the previous section. The measure for attentiveness (*Abs_Area_Under_Curve*) was calculated from an individual's choice responses. Pearson correlations and OLS regression analyses were performed predicting *Abs_Area_Under_Curve* by the other 11 extracted features to explore the individual relationships between attentiveness and mouse movement features. Additionally, OLS regression was used to predict each Big Five personality trait by all 11 mouse features and *Abs_Area_Under_Curve*.

Three partial least squares analyses (PLS) were performed to explore the overall relationships between extracted cursor movement features, attentiveness, and Big Five personality scores. We adopt a multiverse analytical approach here to examine the constraints of the results (Steegen et al., 2016) depending on the specific variables examined. As such, the three analyses differed on the specific input matrices included. Analysis 1) included Big 5 personality measures ~ All 11 mouse movements and attentiveness (*Abs_Area_Under_Curve*), 2) included Big 5 personality measures with Age and Gender ~ All 11 mouse movements and attentiveness (*Abs_Area_Under_Curve*), and 3) included Big 5 personality measures ~ 11 mouse movements only. The primary goal of this work was to specifically identify the relationship between personality traits and mouse movements (Analysis 3), but we reasoned that other demographic factors (age and gender) may influence the overall results. By comparing the results with and without these demographic variables, we can see the extent to which the mouse movement ~ personality relationship is influenced by these variables. Additionally, as the attentiveness measure was not a true "mouse movement" and may be hard to quantify in other tasks (i.e., where deviation from average responding is not possible), we wanted to test whether these results held even when removing this variable.

The PLS analyses were conducted in Matlab 2018b. The current work adapted the Behavioral PLS code from https://www.rotman-baycrest.on.ca/ to be used with two matrices of behavioral data (rather than a matrix of behavioral data and a matrix of brain data, such as fMRI or EEG). Analysis code can be accessed at: https://osf.io/fr74q/. This PLS analysis extracts maximally covarying latent variables from the covariance matrix. In the case of Analysis 3 (Big 5 personality traits and 11 mouse movements), this is the covariance of personality measures (**X** matrix which is 791 participants x 5 personality variables) with a matrix of mouse movement features (**Y** matrix which is 791 participants x 11 mouse movement features) for all participants. Before calculating the covariance matrix, variables were first *z*-scored. Next the covariance matrix was calculated as X'*Y, yielding a 5 x 11 matrix. Subsequently, the singular value decomposition (SVD) was performed on the covariance matrix, X'*Y. The results of the SVD are linear combinations of the two data matrices that maximize their covariance, referred to as latent variables. These extracted latent variables (LVs) are mutually orthogonal to one another.

To estimate the reliability of the latent variables, permutation testing was conducted by first shuffling the order of one of the two input matrices then running SVD on the newly calculated covariance matrix with the shuffled data. This step was repeated 10,000 times to generate a null distribution and by comparing the amount of covariance explained for the original LV compared to the null distribution. From this we could derive a *p*-value, which was estimated for each LV. Next, to test whether the pattern of effects (i.e., the linear combination of variables) were reliable, a bootstrapping procedure was employed where rows (corresponding to participants) were resampled with replacement. The procedure was conducted with 10,000 bootstrapped samples to generate 95% confidence intervals around each of the variables in the LV.

3. Results

3.1. Variable and Sample Descriptives

Table 1 includes descriptive statistics for personality traits and mouse movement features. In terms of mouse movements, on average, participants made re-selection in 33% of attention-check trials and 25% of normal trials. An average participant took around 10 long (> 4 sec) pauses during the entire experiment. In each trial, an average participant fixated on 10 points that accumulated to 7500 milliseconds per trial. Average deviation from randomness (*Abs_Area_Under_Curve*) is 0.22, with a minimum deviation of 0, and maximum deviation of 0.42.

Table 1. Descriptive Statistics of Normalized Personality Traits & Mouse Movement Features

1(a) Descriptive statistics of participant's normalized Big Five personality scores (N=791)

Personality Traits	Mean	Std Deviation	Min	Max
Extraversion	2.82	0.96	1.00	5.00
Agreeableness	3.75	0.73	1.44	5.00
Conscientiousness	3.92	0.77	1.56	5.00
Neuroticism	2.53	0.95	1.00	5.00
Openness	3.61	0.78	1.10	5.00

1(b) Descriptive statistics of participant's mouse movement features (N=791)

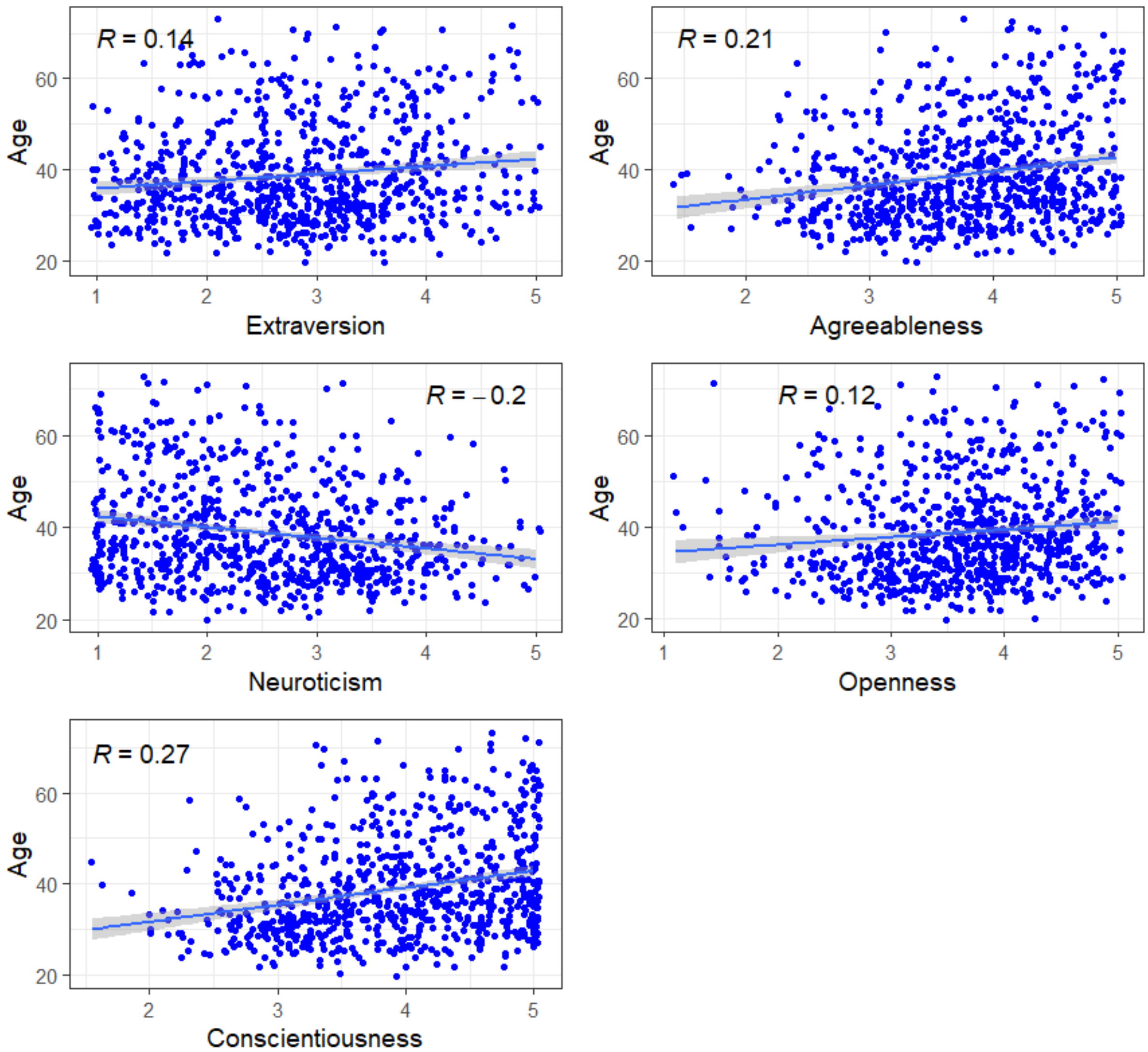
Mouse Movement Features	Mean	Std Deviation	Min	Max
avg_click_att	7.07	1.61	6.00	25.50
reclick_percent_att	0.33	0.21	0.00	1.00
avg_click_norm	5.62	0.72	5.00	14.24
reclick_percent_norm	0.25	0.17	0.00	1.00
avg_euc_dist	5235.33	1613.57	2246.97	15157.24
avg_euc_speed	0.41	0.11	0.14	1.24
avg_completion_time	14849.01	6717.49	8101.91	79774.36
total_pause_cnt	9.46	13.66	0.00	103.00
avg_fixation_dur	868.73	386.60	419.80	3619.54
avg_agg_fixation_dur	7521.76	4169.25	1661.08	32585.53
avg_fixation_cnt	8.75	2.54	2.60	25.96
Abs_Area_Under_Curve	0.22	0.11	0.00	0.42

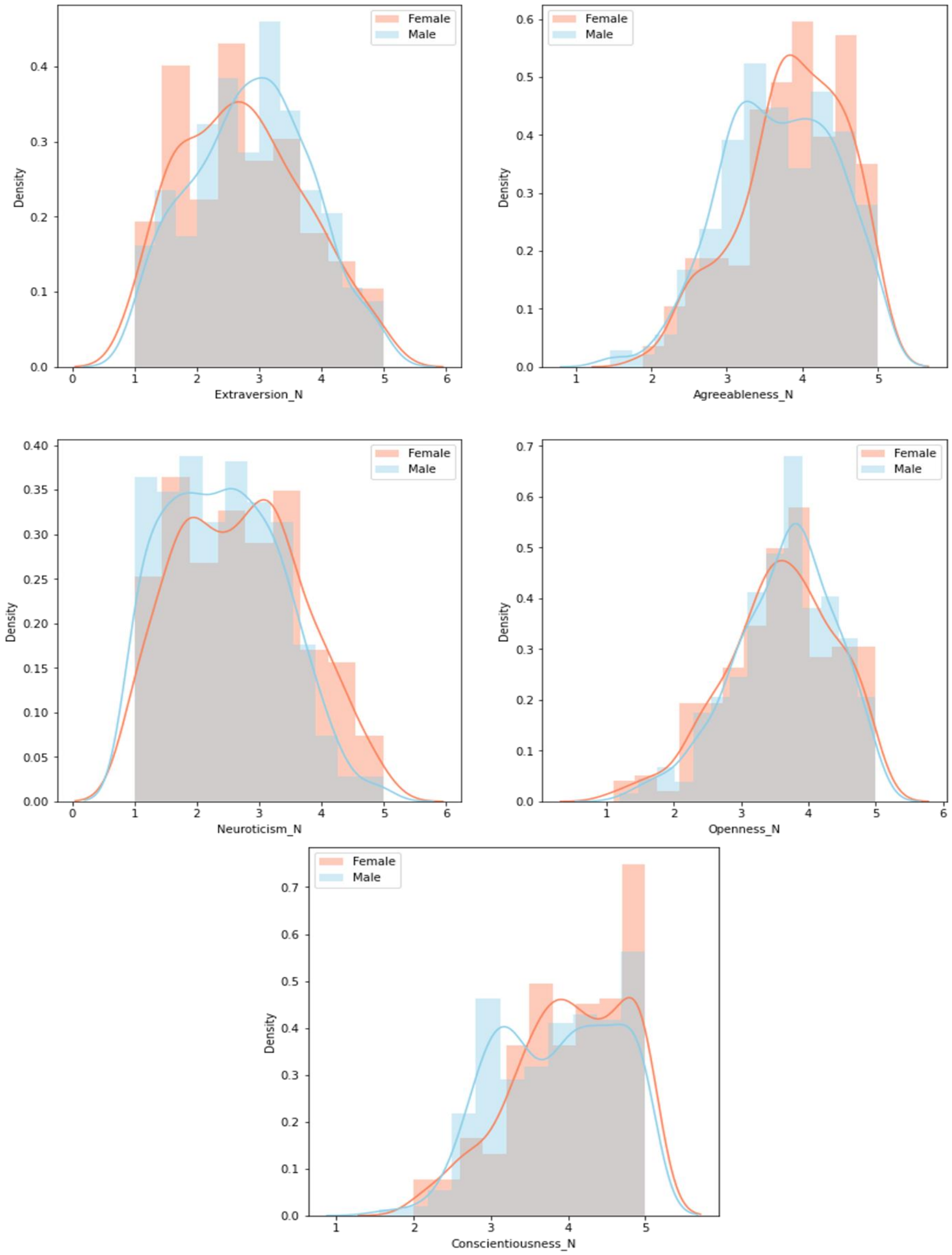
3.2. Data Representativeness

Before performing further analysis, we compared personality distributions of the studies by gender and age with personality distributions found in other literature to examine the representativeness of our data. The distribution of participants' normalized Big Five personality scores by age found in our analysis are similar to the distribution presented in John and Srivastava's research (John & Srivastava, 1999). Differences in personality traits by gender (Costa et al., 2001) and age (Soto et al., 2011) found in our analysis are also supported by previous work. **Figure 2** shows the distribution of personality traits by gender and with age. Age was positively related to

Conscientiousness and Agreeableness, and negatively related to Neuroticism. It also showed weaker positive relationships with Openness and Extraversion. On average, males tend to score higher in Extraversion, and females tend to score higher on Agreeableness, Conscientiousness, and Neuroticism. These results show that the personality distribution of participants in this study is representative of the general population, hence the study's results are generalizable to larger populations.

Figure 2. Distribution of normalized personality scores by age (top) and gender (bottom). *R* reflects correlation coefficients on age ~ personality relationships.





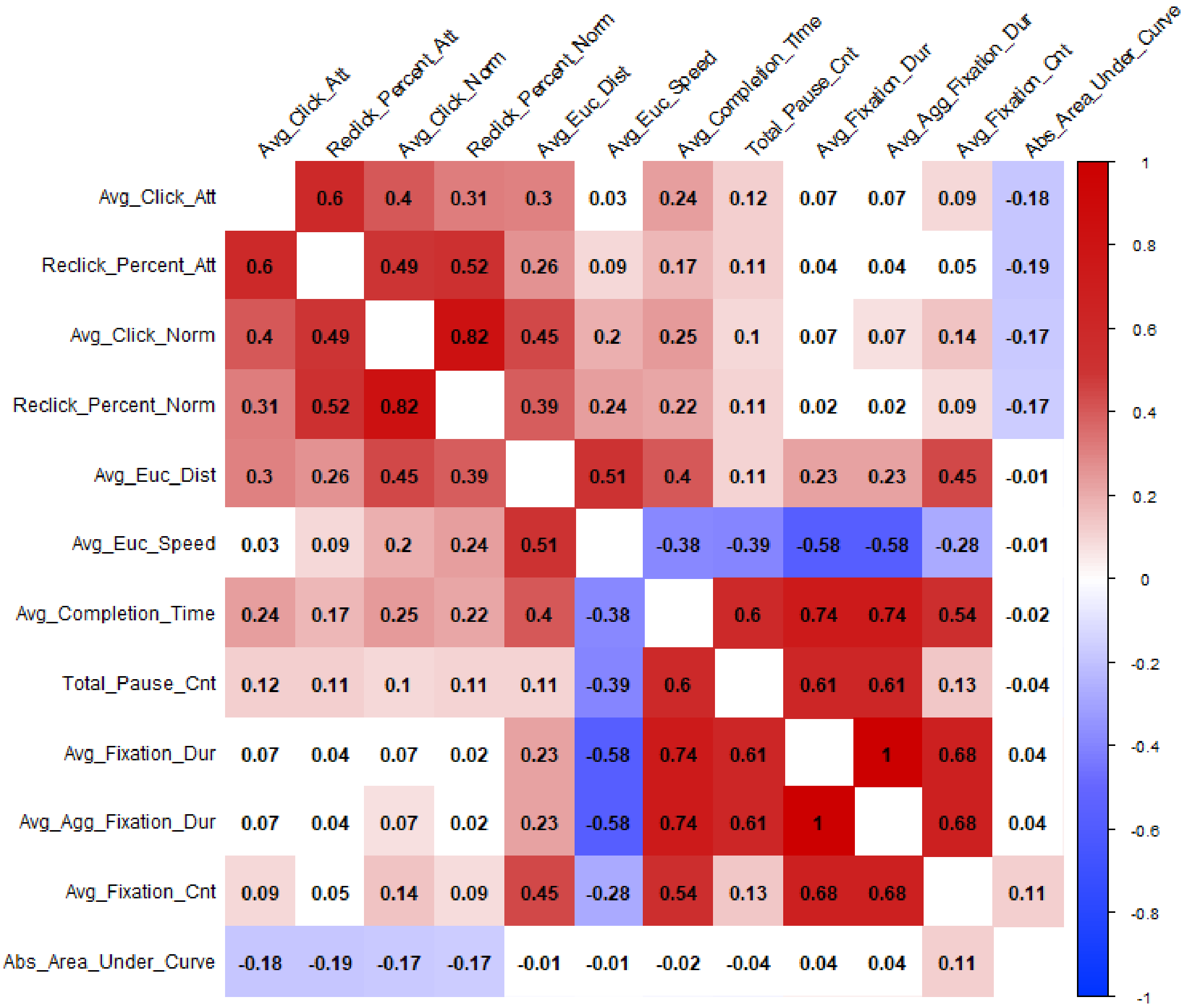
3.3. Univariate Statistical Analyses

3.3.1. Mouse Movements and (In)attentive responding

An initial aim was to test whether mouse movements are predictive of compliance in the online experiment. Our proxy for compliance and task attentiveness is the *Abs_Area_Under_Curve* measure, in which lower values reflect more random responses in the image choice task. The bottom row of **Figure 3** presents correlation results between *Abs_Area_Under_Curve* and the other 11 extracted cursor movement features. Results show that attentive responding is significantly negatively correlated with all click-related features and positively correlated with average number of fixations. When examined via OLS multiple regression (see Supplementary Materials), only average clicks during attention trials was a significant predictor. However, this likely resulted from multicollinearity between click-related features, and as such, the bivariate correlations are shown below.

Figure 3: Bivariate correlations between all Mouse Movements and Attentiveness Measure

White squares reflect that the correlation not significant at uncorrected $p < 0.05$



3.3.2. Mouse Movements, (In)attentive Responding, and Personality

Correlations between mouse movements, inattentive responding, and personality traits are shown in **Table 2.** OLS regressions were also conducted on each of the Big Five personality traits by the 11 mouse movement features and attentiveness to the task (*Abs_Area_Under_Curve)*. [See Supplementary for regression tables]. Only *Abs_Area_Under_Curve* was significantly predictive in the models examining Extraversion (negatively), Openness (positively), and Conscientiousness (positively) in these models. Lower *Abs_Area_Under_Curve* and higher average number of clicks during attention trials were significantly predictive of Neuroticism. Higher *Abs_Area_Under_Curve* and lower average number of clicks during attention trials were predictive of Agreeableness. No other significant relationships were found in these analyses, however, and this was again likely due to multicollinearity of mouse features.

Table 2. Bivariate correlations between mouse movements features & Big 5 personality traits

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
avg_click_att	**0.099****	**-0.085***	**-0.076***	0.062	-0.028
reclick_percent_att	**0.106****	-0.030	-0.049	-0.002	**-0.083****
avg_click_norm	0.025	**-0.073***	**-0.077***	0.031	-0.041
reclick_percent_norm	0.033	**-0.071***	**-0.082***	0.018	-0.065
avg_euc_dist	0.016	0.002	0.014	0.007	0.036
avg_euc_speed	0.003	-0.051	**-0.081***	**0.074***	-0.049
avg_completion_time	0.016	0.026	0.043	-0.047	0.041
total_pause_cnt	0.028	0.014	-0.019	-0.014	-0.002
avg_fixation_dur	-0.003	-0.011	-0.013	0.002	-0.019
avg_agg_fixation_dur	-0.033	0.066	**0.107****	-0.055	**0.078***
avg_fixation_cnt	-0.053	**0.107****	**0.156****	**-0.071***	**0.119****
Abs_Area_Under_Curve	**-0.125****	**0.119****	**0.216****	**-0.098****	**0.117****

* Correlation is significant at the 0.05 level.

** Correlation is significant at the 0.01 level.

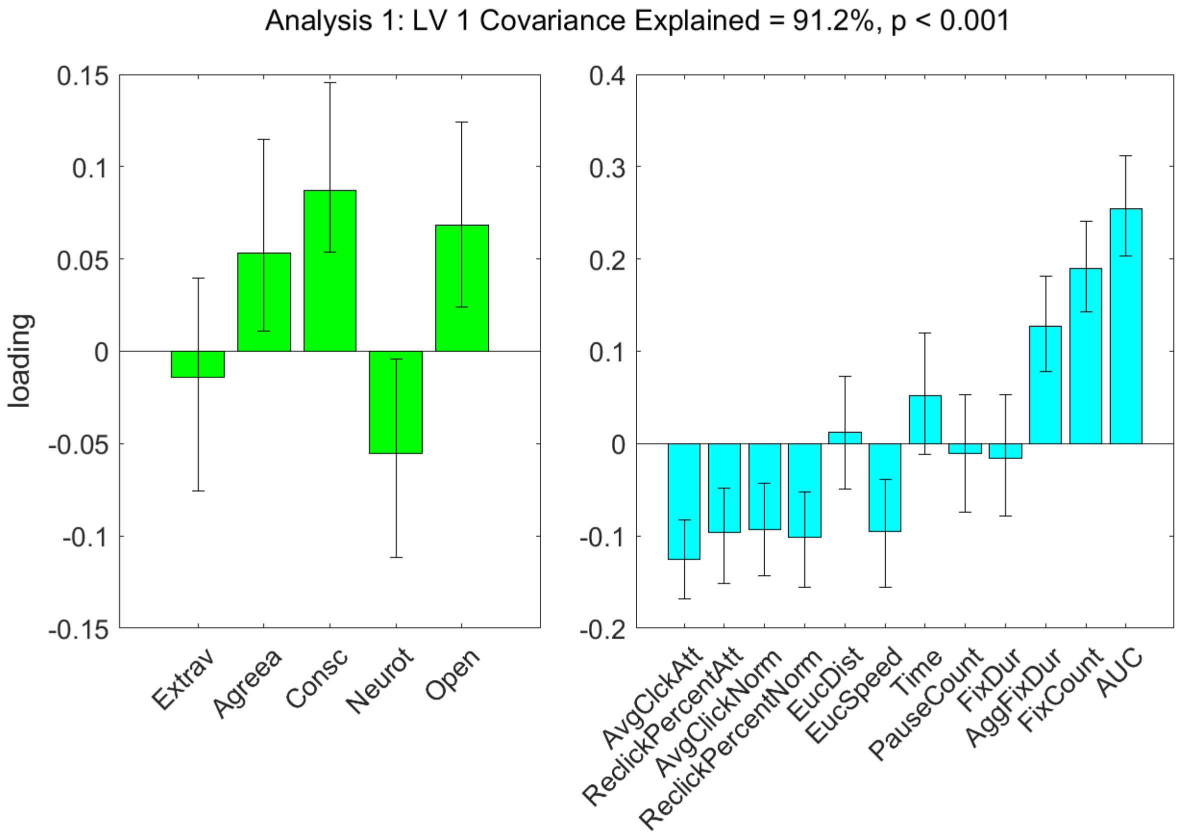
3.4. Multivariate Statistical Analyses

To better examine whether mouse movements can reflect individual differences in personality traits, partial least squares (PLS) analyses were run. The results of the OLS regressions are hard to interpret due to the high intercorrelation between click based measures, leading to multicollinearity in the multiple regression models. In comparison, multicollinearity is not an issue in PLS and this task allows for all of the personality traits to be examined in the same analysis, rather than treating these personality traits as independent. Specifically, this PLS approach allows for the examination of the linear combinations of mouse movements and personality features and can identify the underlying structure of the variables when examined together.

3.4.1. PLS Analysis 1: Big 5 ~ Mouse Movements & AUC

The first latent variable (LV 1) of the PLS analysis was significant (p = 0.001) and explained 91% of the cross-block covariance. **Figure 4** shows the results of LV 1. On the personality side, the first latent variable corresponds to higher Agreeableness, Conscientiousness, and Openness, and lower Neuroticism. On the mouse movement features side, LV1 corresponds to lower number of clicks/re-clicks, lower euclidean speed (i.e., faster mouse movements), longer aggregated fixation durations, more fixations, and less random responding (higher AUC). Euclidean distance, time, pauses, and fixation durations did not show a reliable relationship in LV 1 (as shown by 95% CI bars crossing 0). The relationship between the two sets of variables suggests that participants who are more Agreeable, Conscientious, and Open, and less Neurotic also show mouse movement patterns associated with greater attentiveness and care while doing this task as (i.e., fewer unnecessary clicks, slower movements, more pauses, and less random responding).

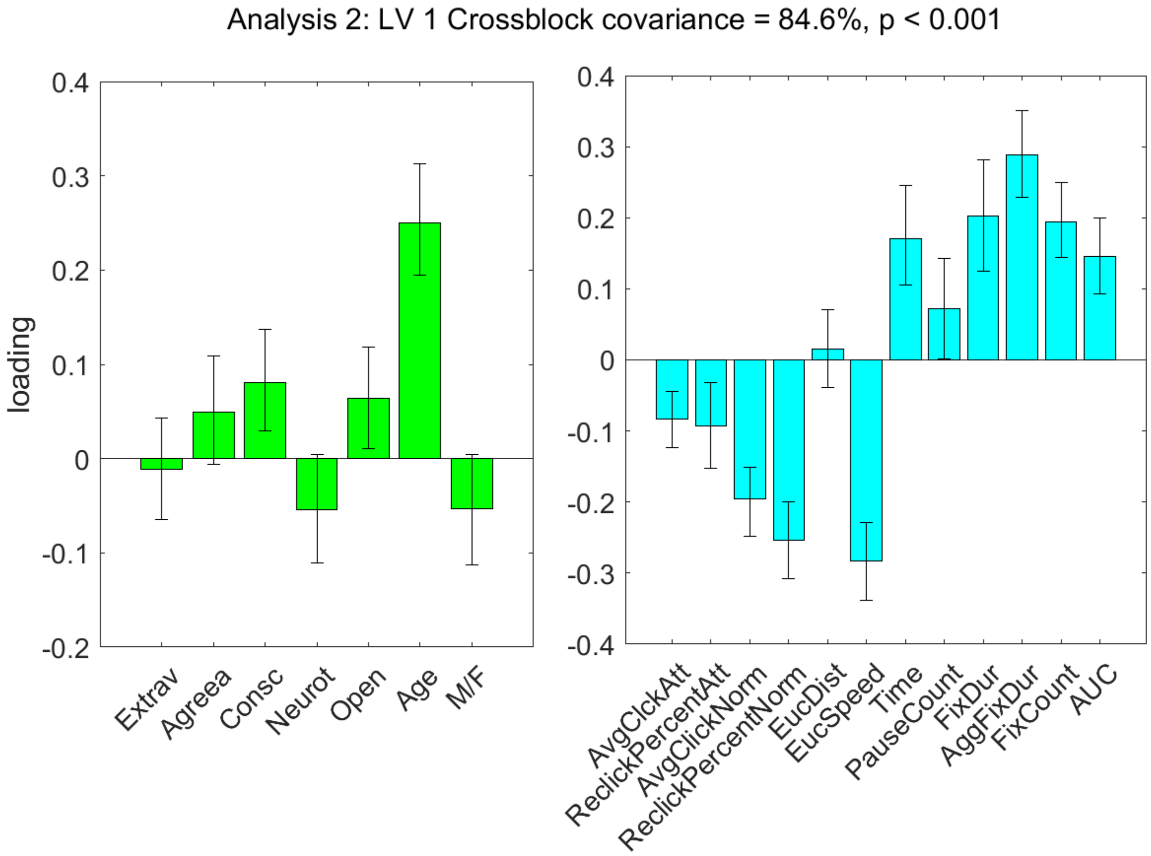
Fig 4: Factor loadings for LV 1 in PLS Analysis 1 (with AUC). Error bars on each of the variables represent 95% confidence intervals based on bootstrapped estimates.



3.4.2. PLS Analysis 2: Big 5 with Demographics ~ Mouse Movements & AUC

When Age and Gender were included in the PLS, the first latent variable (LV 1) of the PLS analysis was significant (p < 0.001) and explained 85% of the cross-block covariance. **Figure 5** shows the results of LV 1. The overall pattern of results was similar to the first PLS analysis. With the inclusion of these demographic variables, Age, Conscientiousness, and Openness showed reliable relationships with almost all mouse features. In these results, being older and scoring higher on Conscientiousness and Openness was associated with less unnecessary clicks, slower mouse movements, more and longer fixations, and greater attentiveness. Relative to Analysis 1, the inclusion of age created more consistent relationships with timing-related features, though fewer personality features showed reliable loadings.

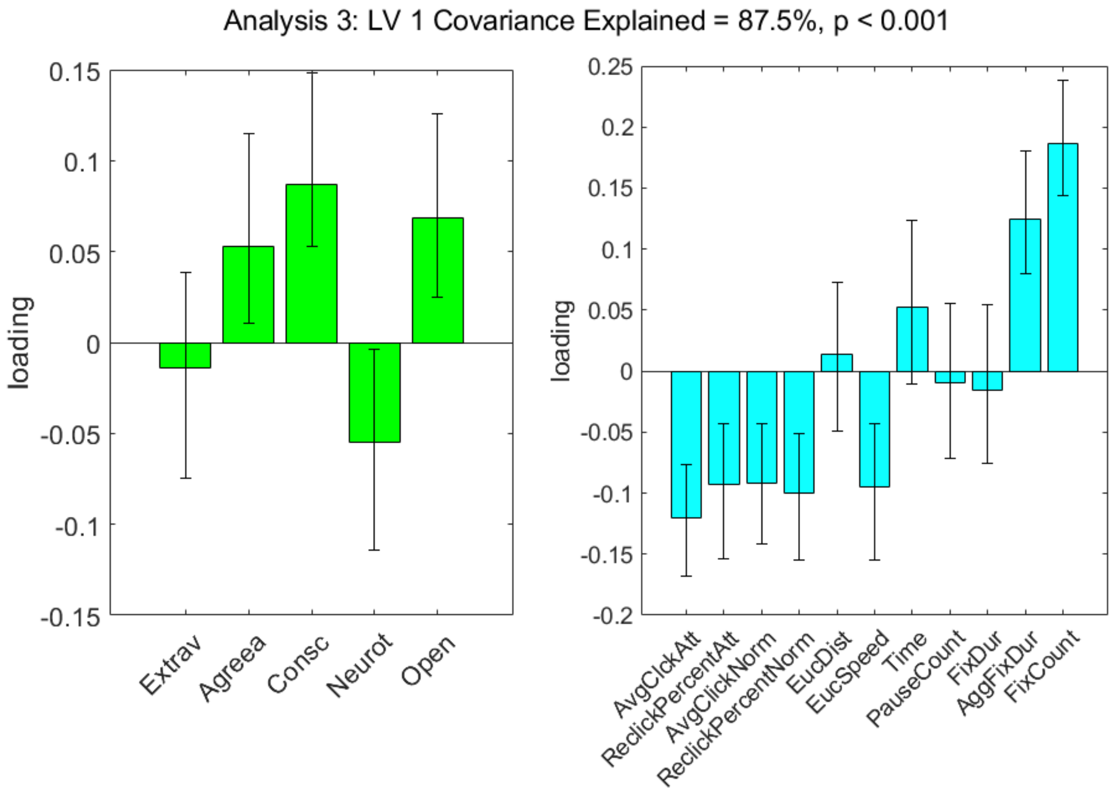
Fig 5: Factor loadings for LV 1 in PLS Analysis 2 (including Demographics & AUC). Error bars on each of the variables represent 95% confidence intervals based on bootstrapped estimates.



3.4.3. PLS Analysis 3: Big 5 ~ Mouse Movements

When AUC was removed from the right-side matrix in the PLS regression, the first latent variable (LV 1) was still significant ($p < 0.001$) and explained 88% of the cross-block covariance. **Figure 6** shows the results of LV 1. The results replicated PLS Analysis 1: even when removing the attentiveness measure (*Abs_Area_Under_Curve*), the combination of high Agreeableness, Conscientiousness, and Openness and low Neuroticism were associated with less unnecessary clicking and more fixations.

Fig 6: Factor loadings for LV 1 in PLS Analysis 3 (Big 5 and Mouse Movements Only). Error bars on each of the variables represent 95% confidence intervals based on bootstrapped estimates.



4. Discussion

The goal of this work was to determine whether mouse movements, on a simple judgment task, could be used to predict individual differences in personality traits as well as compliance and attentiveness in an online experiment. Univariate analyses showed that several click-based mouse movements were related to more attentive and less random responding in this experiment. When examined via OLS regressions, there were relatively weak relationships between mouse movement features and personality traits, and this analysis was hindered by the high intercorrelation between mouse features. However, a much clearer picture was obtained when these features were analyzed using a multivariate analysis technique, in this case, a partial least squares

(PLS) analysis. The PLS results show that a specific linear combination of personality traits (high Agreeableness, Conscientiousness, and Openness, and low Neuroticism) were related to a set of mouse movements reflecting slower and more deliberate responding (less additional clicks and more fixations).

4.1. Personality and Mouse Movements

The key finding of these analyses was that a pattern of mouse movement features that are reasonably interpretable as indicating greater care and attention to the task were associated with the expected personality traits of Conscientiousness, Agreeableness, and Openness, and negatively related to Neuroticism. This general pattern held regardless of whether the attentiveness measure (*Abs_Area_Under_Curve*) was also included in the PLS analysis. Importantly, by approaching this question via a data-driven, multivariate analysis, a clearer and more robust pattern of results was found than what individual OLS regressions showed.

The inclusion of demographic variables (age and gender) changed the PLS results somewhat, though the overall pattern of effects stayed the same. Specifically, including age created stronger links to timing related mouse features, and lessened the role of Agreeableness and Neuroticism. Though participants were not explicitly told to respond quickly, it is possible that the relationship with age and slower mouse movements is due to the observed negative relationship between age and reaction time in other experiments (Fozard et al., 1994). Additionally, previous studies suggest that, in adulthood, Agreeableness increases with age and Neuroticism decreases with age (Soto et al., 2011). Consistent with this, in our sample, age was also positively correlated with Agreeableness (r = 0.21) and negatively related to Neuroticism (r = 0.20). Interestingly, Conscientiousness was positively correlated with age in our sample (r = 0.27) and in previous research (Soto et al., 2011), but remained a reliable loading on the personality side of this PLS analysis. Thus, while these results remained reasonably consistent across all analyses, this analysis demonstrates the utility of a multiverse approach to determine the constraints of an observed statistical relationship and suggests that Conscientiousness is more readily predicted by mouse movements even when age and gender are taken into account.

Based on these results, we propose that researchers interested in using mouse movement features to predict individual differences ought to adopt multivariate analyses that incorporate the underlying structure of the full data and adopt a multiverse analytic approach if applicable. While the current work only examined personality as measured by the Big Five Inventory (John & Srivastava, 1999), it is very likely that other individual differences may show interesting relationships when examined in this way. Additionally, while this study demonstrates the feasibility of inferring trait-level information about participants based on mouse movements, an exciting future direction would be to relate this to state-level differences in affect, fatigue, or other factors of interest to researchers.

4.2. Evaluation of Attentiveness

The results shown in Table 3 demonstrate significant negative correlations between attentiveness (*Abs_Area_Under_Curve*) and all click-related features at $\alpha = 0.01$. These results provide an important insight - that click-rate alone may also be a good indicator of inattentiveness. Intuitively, more clicking can mean impatience or random clicking, which in turn leads to more inattentive or random responding. These results can significantly contribute to using mouse movement to filter out inattentive responding in online research.

4.3. Limitations

While significant relationships were found between cursor movement features, attentiveness, and personality traits, a limitation associated with the study is that these data all come from a choice-based image rating task. Therefore, the specific pattern of mouse movements identified here may not generalize to other tasks. Future work should further examine these relationships in different settings to gain more comprehensive insights on how to accurately infer internal traits based on cursor movement features. More targeted tasks can also be developed to examine specific correlation between features and personality traits. However, this work does show the feasibility of using mouse movements with multivariate approaches to predict personality traits and task attentiveness. Additionally, as the study was not initially designed for mouse movement analysis, we did not record the different types of cursor devices used by our participants (e.g., touch pad vs an actual mouse). Different types of devices might lead to variation in the raw data captured. Future work should make note of this nuisance and separate users' devices for further analysis.

4.4 Conclusion

This research aimed to investigate the relationship between mouse movement patterns, attentiveness, and personality traits. Multivariate analysis showed that features extracted from mouse movement data during a simple image rating task are significantly correlated with a participant's Big Five personality traits. Additionally, attentiveness, as captured by individual response's deviation from random responding, is significantly related to all five personality dimensions, and with cursor movement features such as fixations and click rates. PLS analysis results showed significant underlying relationships between cursor features, attentiveness and personality traits that allow researchers to clearly separate Agreeableness, Openness, and Conscientiousness from Neuroticism. A compelling implication from this work is that researchers may be able to infer individuals' personality characteristics without explicitly asking about them, even in tasks that are not designed to evaluate personality, such as the simple image choice task used here. Going forward, this work demonstrates researchers across academic and consumer sectors may be able to leverage multivariate analyses with mouse movements to infer a variety of individual differences.

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Data & Code Availability Statement

- Python code for initial data processing/cleaning, QA checks, correlation, and correlation analyses available at https://github.com/tianyueniu/mouse_movement_personality
- Data aggregated across studies with identifiers removed: https://github.com/tianyueniu/mouse_movement_personality/blob/master/personality_mouse_final_table.csv
- A demo of the image rating task is available at: https://kywch.github.io/ImageRatingStudy/multi-image-rating-demo.html
- Matlab code for multivariate (PLS) analysis, R code for figure generation, and relevant data files available at the OSF project page: https://osf.io/fr74q/

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Supplementary: Results of OLS Regressions

OLS Regression predicting Attentiveness (Abs_Area_under_Curve) from Mouse Movements

Table 2: OLS Regression predicting Attentiveness from Mouse Movements

	coef	std error	t	P > I t I
intercept	**0.2175****	0.004	55.867	0.000
avg_click_att	**-0.012***	0.005	-2.279	0.023
reclick_percent_att	-0.008	0.005	-1.443	0.150
avg_click_norm	-0.008	0.007	-1.045	0.297
reclick_percent_norm	-0.007	0.007	-0.990	0.322
avg_euc_dist	-0.005	0.009	-0.487	0.626
avg_euc_speed	0.011	0.010	1.097	0.273
avg_completion_time	-0.002	0.007	-0.312	0.755
total_pause_cnt	0.005	0.006	0.804	0.422
avg_fixation_dur	-0.017	0.010	-1.716	0.087
avg_agg_fixation_dur	0.016	0.015	1.087	0.277
avg_fixation_cnt	0.012	0.010	1.138	0.255

R-squared: 0.080

*Coefficient is significant at the 0.05 level.

**Coefficient is significant at the 0.01 level.

OLS Regression predicting Personality traits from Mouse Movements & Attentiveness
Regression results predicting each of the Big Five Factors by all mouse movement features and task attentiveness. *Coefficient is significant at the 0.05 level. **Coefficient is significant at the 0.01 level.

(a) Extraversion

	coef	std error	t	P > | t |
intercept	2.818	0.034	82.953	0.000
avg_click_att	0.033	0.046	0.714	0.476
reclick_percent_att	0.077	0.047	1.629	0.104
avg_click_norm	-0.062	0.065	-0.959	0.338
reclick_percent_norm	0.002	0.065	0.028	0.978
avg_euc_dist	0.109	0.083	1.315	0.189
avg_euc_speed	-0.111	0.083	-1.337	0.182
avg_completion_time	0.013	0.063	0.212	0.832
total_pause_cnt	0.022	0.053	0.415	0.678
avg_fixation_dur	-0.036	0.086	-0.416	0.678
avg_agg_fixation_dur	-0.055	0.130	-0.426	0.670
avg_fixation_cnt	-0.088	0.091	-0.965	0.335
Abs_Area_Under_Curve	**-0.099****	0.035	-2.790	0.005

R-squared: 0.032

(b) Openness

	coef	std error	t	P > | t |
intercept	**3.610****	0.027	131.69	0.000
avg_click_att	0.016	0.037	0.430	0.668
reclick_percent_att	-0.059	0.038	-1.549	0.122
avg_click_norm	0.010	0.052	0.199	0.842
reclick_percent_norm	-0.028	0.052	-0.536	0.592
avg_euc_dist	0.069	0.067	1.033	0.302
avg_euc_speed	-0.072	0.067	-1.078	0.281
avg_completion_time	-0.036	0.050	-0.711	0.477
total_pause_cnt	-0.007	0.043	-0.158	0.875
avg_fixation_dur	-0.116	0.070	-1.668	0.096
avg_agg_fixation_dur	0.132	0.105	1.255	0.210
avg_fixation_cnt	-0.023	0.073	-0.314	0.753
Abs_Area_Under_Curve	**0.069***	0.029	2.426	0.016

R-squared: 0.036

(c) Conscientiousness

	coef	std error	t	P > | t |
intercept	**3.916****	0.027	147.74	0.000
avg_click_att	-0.050	0.036	-1.416	0.157
reclick_percent_att	0.042	0.037	1.131	0.258
avg_click_norm	-0.027	0.050	-0.543	0.587
reclick_percent_norm	-0.020	0.051	-0.390	0.697
avg_euc_dist	0.057	0.065	0.883	0.378
avg_euc_speed	-0.083	0.065	-1.284	0.200
avg_completion_time	-0.032	0.049	-0.661	0.509
total_pause_cnt	-0.047	0.042	-1.118	0.264
avg_fixation_dur	-0.116	0.067	-1.725	0.085
avg_agg_fixation_dur	0.168	0.101	1.656	0.098
avg_fixation_cnt	-0.018	0.071	-0.251	0.802
Abs_Area_Under_Curve	**0.1424****	0.028	5.151	0.000

R-squared: 0.078

(d) Neuroticism

	coef	std error	t	P > | t |
intercept	**2.525****	0.034	74.880	0.000
avg_click_att	**0.104***	0.045	2.311	0.021
reclick_percent_att	-0.080	0.047	-1.691	0.091
avg_click_norm	0.042	0.064	0.660	0.509
reclick_percent_norm	-0.022	0.064	-0.343	0.732
avg_euc_dist	-0.096	0.082	-1.165	0.244
avg_euc_speed	0.161	0.083	1.945	0.052
avg_completion_time	-0.014	0.062	-0.229	0.819
total_pause_cnt	0.018	0.053	0.330	0.741
avg_fixation_dur	0.107	0.086	1.247	0.213
avg_agg_fixation_dur	-0.057	0.129	-0.439	0.661
avg_fixation_cnt	0.055	0.090	0.611	0.541
Abs_Area_Under_Curve	**-0.082***	0.035	-2.341	0.019

R-squared: 0.028

(e) Agreeableness

	coef	std error	t	P > | t |
intercept	**3.754****	0.026	145.19	0.000
avg_click_att	**-0.076***	0.035	-2.192	0.029
reclick_percent_att	0.060	0.036	1.659	0.098
avg_click_norm	-0.020	0.049	-0.416	0.677
reclick_percent_norm	-0.039	0.049	-0.799	0.425
avg_euc_dist	0.014	0.063	0.222	0.824
avg_euc_speed	-0.027	0.063	-0.419	0.675
avg_completion_time	-0.016	0.048	-0.345	0.730
total_pause_cnt	0.033	0.041	0.807	0.420
avg_fixation_dur	-0.046	0.066	-0.698	0.485
avg_agg_fixation_dur	0.012	0.099	0.118	0.906
avg_fixation_cnt	0.068	0.069	0.979	0.328
Abs_Area_Under_Curve	**0.064***	0.027	2.387	0.017

R-squared: 0.036