Modelling Personality Change During Extreme Exogenous Conditions

A Bayesian Study On Social Media Language During The First Wave of the COVID-19 Pandemic

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Abstract

Personality traits change over time, however research on it was sparse, since previous approaches were too time-consuming and expensive. Also, the necessary methodological complexity was beyond the capabilities of classical personality researchers, which resulted in contradictory results and lack of methodological standards. In this paper, we presented a simple and cost-effective method that overcame these restrictions.

We introduced a machine learning approach for daily measurements to personality research, and developed a bespoke Bayesian algorithm to analyse the observed change. This resulted in uncovering concrete points of regime-shift that overlapped with relevant exogenous events for a Japanese sample of social media users.

With it, we showed that personality measures displayed significant elasticity under extreme exogenous conditions during the first wave of COVID-19 and the subsequent societal countermeasures, which can be interpreted as a temporary shift from normal expression of latent psychological traits z to their respective emergency expression z_e .

Concretely, we found that the group of top 25% Conscientiousness users displayed a significant change in the FFM factors Agreeableness and Extraversion. We finally compared our findings with those from similar studies in other cultures, and discussed generalisability as well as future qualitative and quantitative directions for research.

Keywords— COVID-19, Personality Change, Psychometrics, Five Factor Model, Bayesian Statistics

1. Introduction

Amidst the COVID-19 pandemic, societies world-wide faced a crisis unprecedented to the modern world outside wartime. Borders were closing, international travel was restricted, and entire regions and countries were locked-down. To curb the pandemic, curfews were imposed that resulted in hardship and uncertainties for populations, which had to live in isolation, fear, economic straits, and frustration (Muñoz-Fernández and Rodríguez-Meirinhos, 2021). Societies world-wide shifted to an online-first mode that lacked social interaction and came with dangers of being exposed to a dense mesh of fake news and conspiracy theories, which further undermined mutual trust (Limaye et al., 2020; Melki et al., 2021).

Extreme Exogenous Conditions

In this sudden change of environments, the perception, cognition, and behaviour of people changed dramatically, as well (Hino and Asami, 2021; Kashima and Zhang, 2021; Nagata et al., 2021; Tanaka and Okamoto, 2021). This can be interpreted as entering an 'emergency mode', in which they behaved and communicated differently. Behavioural changes to a comparable degree occurred after personal tragedies (Mechanic, 1986), natural disasters (Savage, 2019; Weisæth, 1989),

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¹The authors thank Christopher Demetrakos, KC Chan, Shannen Romero-Perez, and Yoshiki Matsubara for data science support, as well as Yuhong Chen, Renyi Qu, and Julian Kota Kikuchi for additional statistical analyses.

as well as laboratory studies that simulated a common enemy (Jaegher, 2021). In one of these studies, the mere presence of danger made people search for more physical proximity and communicate more. Such effects occurred in other hominidae, as well, and seemed to serve as survival behaviour (Brooks et al., 2021).

People communicated differently in an emergency mode, as well, for example during natural disasters (Finau et al., 2018). Due to wide-spread social networking services (SNS) adaptation (Bayer et al., 2020), this change in communication modified the overall information-field during the pandemic, and furthered the effects of the pandemic on individuals that practiced social distancing and spent most of their time online (Yamamoto et al., 2020). This aggregation of effects may have been so severe that even changes in personality, which were traditionally considered to be rather slow and small over a lifetime (Bleidorn et al., 2021), became more drastic and prevalent in a much smaller time-window.

Indication for personality change

However, literature on this change process was sparse, since traditional research methods were time-consuming and expensive. Latest research on personality research indicated that personality traits indeed tended to change over time and towards greater maturity, whereby in young and late adulthood, the strongest changes occurred. This change was based on genetic, psychological, and environmental components, and displayed individual differences in "rate, timing, and direction of personality trait change" (p. 2). While both understanding about processes and strong theories did not exist yet, more research has been conducted about sources of personality change. For example, significant life events, therapies, and exogenous shocks resulted in changed personality traits. However, the speed and even direction of it displays strong interpersonal and intergroup differences. Also, results on major traumatic events were not consistent, which partly can be contributed to methodological complexities previously unknown to personality research. Top personality researchers called therefore recently for more rigorous longitudinal studies, whereby a special emphasis should be put on time analysis and new forms of measurement. Measures should be more frequent – up to becoming continuous time series, and classical monomethod studies that vastly relied on self-report surveys should be augmented with multimethod approaches; focusing on more natural events like the COVID-19 pandemic. Also, this research should be conducted cross-cultural to better explore generalisability (Bleidorn et al., 2021).

We found two breakthrough studies aligned with that call. First, Sutin et al. (2020) conducted a survey-based study with a pre-posttest design that was conducted in the middle of the first wave of COVID-19 – 'late January and early February 2020 and then again in mid-March 2020' (p. 2), thus spanning approximately six weeks. Their sample was stratified to the population of the United States of America in age, gender, and ethnicity. Against their pre-registered expectations, they found that Neuroticism slightly decreased among those people that were in quarantine or isolation. Furthermore, they found with some individuals isolation to moderate decline in Openness, Agreeableness, and Conscientiousness, especially in the sub-scales 'curiosity', 'trust', and 'organisation', which they contributed to the change in circumstances of the respective individuals. Finally, they found that in working-age adults the sub-scale 'dutifulness' for Conscientiousness decreased due to one item about going to work/ school when not feeling well, which reversed its meaning under these extreme exogenous events. Second, Ahmed et al. (2020) used a machine learning approach on a random sample of Twitter-using health workers that were affiliated with various hospitals around the United States of America, whom they manually identified. They analysed both what the Twitter users 'tweeted' about, using Latent Dirichlet Allocation (LDA) and a topic-over-time (TOT) model, and how their personality changed during the first wave of COVID-19, using the application processing interface (API) from IBM Watson Personality Insights. For that, they divided the data into two blocks: before the pandemic (before February 2020), and during the pandemic (February to April 2020). Contradicting with Sutin et al. (2020), they found significant changes in all facets of the Five Factor Model (FFM): Openness and Agreeableness decreased, whereas Conscientiousness, Extraversion, and Neuroticism increased.

New modelling methods for personality change are needed

What both studies had in common was the notion of extreme exogenous events that influenced the expression of personality directly on a state or trait level, or indirectly through changing the validity of the instruments. For example, existing scales could have been reinterpreted by test-takers due to changing circumstance, or the use of words could have been altered, which changed the measurements of the machine learning approach. Since no confirmatory repetition study existed, this was hard to tell. Also, both studies focused on the time before and during the first wave of COVID-19. However, it was unclear what happened during or after the first wave. Finally, both studies focused on the United States of America and therefore displayed a selection bias. To confirm, whether this phenomenon of personality change was generalisable, one had to test another population with little exposure to the English language and its information-field, yet under the same contextual

embedding of an industrialised nation affected by COVID-19. One had to use more precise and granular measures in an non-intrusive, natural experimental setting, to replicate the serendipitous circumstances of the first survey where participants were surprised by a request for a second survey (Sutin et al., 2020), and the non-intrusive nature of the second survey (Ahmed et al., 2020). Optimally, this took place in a country that was vastly secluded, yet had a wide-spread use of SNS, which acted as a 'quasi-laboratory'. Finally, one had to combine the psychometric rigour from Sutin et al. (2020) with the forward-looking and progressive machine learning approach from Ahmed et al. (2020). Japan could be such a country.

Takeshimura (2020) found that Japanese media users dynamically reacted to COVID-19-related news. They concluded that the public perception of the information field followed dynamic spatiotemporal patterns. In congruence with former models that connected narrative flow with mass psychological phenomena (Houghton et al., 2013), they further concluded that acceleration and velocity of the social attention to risks was influenced by the history of the information flow and existence of alternative narratives. While they mainly focused on news coverage, research about the usage of Twitter in Japan indicated that it was used as a quick tool for information spreading, before other media was consumed. While this bore the opportunity for abuse for spreading fake news, "Twitter became the supplier of information and knowledge for the citizens ... in the early days of the disaster and also the basis for building social capital." (p. 33) (Kaigo, 2012). We concluded that first, this dynamic, psychophysical approach was another indication that a machine-learning-driven psycholinguistic study on the effects of extreme exogenous conditions on personality change within Japanese SNS users was indicated, and second that Twitter was a good medium for that.

Digital Footprints from SNS were proven to be valuable for social research. By applying machine learning, it was possible to deduce personality (Kosinski et al., 2015), gender and age (Koch et al., 2020), and the "hopes and dreams, preferences and motivations, social connections, daily routines, and physical whereabouts" (p.5) (Stachl et al., 2021) of its users. Research on data from Twitter was well established in behavioural research, and it showed to be effective in deducing personality, age, and gender (Schwartz et al., 2013). While daily granularity of Twitter data suggested the use of time series methodology with, this has surprisingly not been exploited by computational social sciences yet. Beyond the novelty of feature extraction and prediction of latent traits, usual approaches were to take the outcomes from advanced methods, and then deploy them in an old fashioned and shallow way, for example using ANOVA (Sutin et al., 2020) or t-tests (Ahmed et al., 2020). This means that a lot of dimensionality of the data got lost in this process. Also, most established methods of analyses, which were overwhelmingly based on various forms of regression analysis, classification or prediction, fell short to provide understanding about both the nature and the timing of dynamic changes. We therefore decided to use Bayesian methodology to analyse the changes in a more dynamic way that also captured additional dimensionality.

2. Empirical Strategy and Model Specification

Bayesian Analysis is based on updating the joint posterior density of parameters based on observed data. Unlike frequentist methods, it does not rely on point estimates, but focuses on the joint posterior distribution, whereby the summary statistics conveys useful insights about the parameters. This makes it useful in situations with restricted data availability and outcomes that are fundamentally probabilistic in nature, which is the case in human behaviour (Fox, 2010; Nakatsuma, 2007). Also, the prior specification of models allows the injection of insights from existing theories, which is central in behavioural research, while still allowing to learn from data, thus merging bottom-up practicality from machine learning with theory-driven top-down precision. Though it has been successfully used in psychometrics before (Natesan et al., 2016), it neither is wide-spread in psychometrics nor in computational social sciences. The authors hope to introduce this methodology to the wider research community.

2.1. Flexible Bayesian Modeling of Finite Discrete Distributions

Suppose we have n days in the data set and they are categorised into k groups. Define a label for grouping as

$$x_i = j, \quad i = 1, \dots, n, \quad j = 1, \dots, k, \quad (1)$$

and the probability that we pick the day i from group j as

$$\Pr\{x_i = j\} = p_j, \quad 0 \leq p_j \leq 1, \quad \sum_{j=1}^k p_j = 1. \quad (2)$$

We may suppose the probability p_j is determined by a parametric model (e.g., binomial distribution) when the label x_j can be regarded as an integer j . Although such a parametric assumption may ease the estimation procedure for discrete data

$(x_1, \dots, x_n)$, it lacks flexibility and applicability to more general data sets. Therefore, we will not impose upon any specific parametric structure on $(p_1, \dots, p_k)$ and assume a more flexible prior for them instead. In our study, we use the following Dirichlet distribution:

$$(p_1, \dots, p_k) \sim \text{Dirichlet}(\alpha_1, \dots, \alpha_k), \quad (3)$$

as the prior for $(p_1, \dots, p_k)$. The p.d.f. of the Dirichlet distribution is

$$p(p_1, \dots, p_k) = \frac{\prod_{j=1}^k p_j^{\alpha_j-1}}{B(\alpha_1, \dots, \alpha_k)}, \quad B(\alpha_1, \dots, \alpha_k) = \frac{\prod_{j=1}^k \Gamma(\alpha_j)}{\Gamma(\sum_{j=1}^k \alpha_j)}, \quad (4)$$

where $B(\cdot)$ is the multivariate beta function and $\Gamma(\cdot)$ is the gamma function.

The likelihood of $(p_1, \dots, p_k)$ given $(x_1, \dots, x_n)$ is

$$p(x_1, \dots, x_n | p_1, \dots, p_k) = \prod_{j=1}^k p_j^{y_j}, \quad y_j = \sum_{i=1}^n \mathbf{1}(x_i = j), \quad (5)$$

where $\mathbf{1}(\cdot)$ is the indicator function that is equal to one if the expression inside the parentheses is true; otherwise, it is zero. Thus y_j is the number of days who are categorised into group j in the data set. By applying Bayes' theorem, the posterior distribution of $(p_1, \dots, p_k)$ is obtained as

$$\begin{aligned} p(p_1, \dots, p_k | x_1, \dots, x_n) &= \frac{p(x_1, \dots, x_n | p_1, \dots, p_k) p(p_1, \dots, p_k)}{p(x_1, \dots, x_n)} \\ &= \frac{\prod_{j=1}^k p_j^{y_j + \alpha_j - 1}}{B(y_1 + \alpha_1, \dots, y_k + \alpha_k)}, \end{aligned} \quad (6)$$

which is also a Dirichlet distribution. Since the mean of the Dirichlet distribution (6) is

$$E[p_j | x_1, \dots, x_n] = \frac{y_j + \alpha_j}{\sum_{j'=1}^k (y_{j'} + \alpha_{j'})}, \quad j = 1, \dots, k, \quad (7)$$

it can be interpreted as a Bayesian counterpart to a histogram.

For later use, we derive the marginal likelihood for the Dirichlet model. By using the identity

$$\begin{aligned} p(p_1, \dots, p_k | x_1, \dots, x_n) &= \frac{p(x_1, \dots, x_n | p_1, \dots, p_k) p(p_1, \dots, p_k)}{p(x_1, \dots, x_n)} \\ \Rightarrow p(x_1, \dots, x_n) &= \frac{p(x_1, \dots, x_n | p_1, \dots, p_k) p(p_1, \dots, p_k)}{p(p_1, \dots, p_k | x_1, \dots, x_n)}, \end{aligned} \quad (8)$$

the marginal likelihood is derived as

$$p(x_1, \dots, x_n) = \frac{B(y_1 + \alpha_1, \dots, y_k + \alpha_k)}{B(\alpha_1, \dots, \alpha_k)}. \quad (9)$$

2.2. Regime Shifts in Finite Discrete Distributions

Suppose days in the data set are not homogeneous but they belong to two subpopulations with different probabilities in (2). Without any loss of generality, suppose the first $\tau - 1$ days belong to one subpopulation and the last $n - \tau$ days belong to the other, that is,

$$\Pr\{x_i = j\} = \begin{cases} p_{1j}, & (1 \leq i < \tau); \\ p_{2j}, & (\tau \leq i \leq n). \end{cases} \quad (10)$$

We call τ the change point and suppose it is unknown.

For a fixed τ , the likelihood is given by

$$\begin{aligned} p(x|\tau) &= p(x_1, \dots, x_{\tau-1} | p_{11}, \dots, p_{1k}) p(x_\tau, \dots, x_n | p_{21}, \dots, p_{2k}) \\ &= \prod_{j=1}^k p_{1j}^{y_{1j}(\tau)} p_{2j}^{y_{2j}(\tau)}, \end{aligned} \quad (11)$$

where $x = \{x_i\}_{i=1:n}$ and

$$y_{hj}(\tau) = \begin{cases} \sum_{i=1}^{\tau-1} \mathbf{1}(x_i = j), & (h = 1), \\ \sum_{i=\tau}^n \mathbf{1}(x_i = j), & (h = 2). \end{cases}$$

Therefore, with the prior

$$(p_{h1}, \dots, p_{hk}) \sim \text{Dirichlet}(\alpha_{h1}, \dots, \alpha_{hk}), \quad h = 1, 2, \quad (12)$$

the conditional posterior distribution given τ is derived as

$$\begin{aligned} p(p_{11}, \dots, p_{1k}, p_{21}, \dots, p_{2k} | x, \tau) &= p(p_{11}, \dots, p_{1k} | x, \tau) p(p_{21}, \dots, p_{2k} | x, \tau) \\ &= \frac{\prod_{j=1}^k p_{1j}^{y_{1j}(\tau) + \alpha_{1j} - 1}}{B(y_{11}(\tau) + \alpha_{11}, \dots, y_{1k}(\tau) + \alpha_{1k})} \times \frac{\prod_{j=1}^k p_{2j}^{y_{2j}(\tau) + \alpha_{2j} - 1}}{B(y_{21}(\tau) + \alpha_{21}, \dots, y_{2k}(\tau) + \alpha_{2k})}, \end{aligned} \quad (13)$$

which is the product of two Dirichlet distributions. Thus the marginal likelihood for τ is

$$p(x|\tau) = \frac{B(y_{11}(\tau) + \alpha_{11}, \dots, y_{1k}(\tau) + \alpha_{1k})}{B(\alpha_{11}, \dots, \alpha_{1k})} \times \frac{B(y_{21}(\tau) + \alpha_{21}, \dots, y_{2k}(\tau) + \alpha_{2k})}{B(\alpha_{21}, \dots, \alpha_{2k})}. \quad (14)$$

In the Bayesian framework, we can derive the posterior distribution of the change point τ . Suppose, periods between t_1 and t_2 are the candidates for the change point τ . Since the marginal likelihood for τ ($t_1 \leq \tau \leq t_2$) is given by $p(x|\tau)$ in (14), by applying Bayes' theorem, we obtain the posterior distribution of τ as

$$p(\tau|x) = \frac{p(x|\tau)p(\tau)}{\sum_{s=t_1}^{t_2} p(x|s)p(s)}, \quad (15)$$

where $p(\tau)$ is the prior distribution of the change point. In practice, we often assume the uniform prior over $(t_1, \dots, t_2)$. In this case, we have

$$p(\tau|x) = \frac{p(x|\tau)}{\sum_{s=t_1}^{t_2} p(x|s)}. \quad (16)$$

Finally, we obtain the posterior distribution of $(p_{h1}, \dots, p_{hk})$ ($h = 1, 2$) as

$$p(p_{h1}, \dots, p_{hk} | x) = \sum_{s=t_1}^{t_2} \frac{\prod_{j=1}^k p_{hj}^{y_{hj}(s) + \alpha_{hj} - 1}}{B(y_{h1}(s) + \alpha_{h1}, \dots, y_{hk}(s) + \alpha_{hk})} p(\tau|x), \quad (17)$$

which is a mixture of Dirichlet distributions. As a result, the posterior mean of (17) is a weighted average of (7), i.e.,

$$E[p_{hj} | x_1, \dots, x_n] = \sum_{s=t_1}^{t_2} \frac{y_{hj}(s) + \alpha_{hj}}{\sum_{j'=1}^k (y_{hj'}(s) + \alpha_{hj'})} p(s|x), \quad j = 1, \dots, k, \quad h = 1, 2. \quad (18)$$

One of the base assumptions in psychometrics is that any measured psychological latent trait z is composed of the real value v and a measurement error ϵ . Since this error is subject to various influences outside and inside the individual (Rust and Golombok, 2014), we can further assume that a series of m measurements will result each time in a slightly different measured latent trait z , the so called *state* s . Given sufficient frequent measurements m , and assuming that no priming, experimental bias, or memory effect took place, we assumed the states s in a within-subject design to result in a prior distribution that resembles a stationary fluctuation around the real value z .

3. Methodology

Modelling emergency expressions of personality traits

If this hypothesis held true, the individuals were not homogeneous but belonged to various subpopulations, of which some displayed a change in expressed personality under extreme exogenous conditions. Once these conditions occurred, we assumed the stationary fluctuation of the relevant subpopulation to change around a different latent trait z_e , denoting the emergency expression e of the normal expression z . As described in the model specification, we assumed that this change from z to z_e to happened around the regime shift point τ , which represented that point in time, when the very same group of persons would be confronted with an exogenous shock in form of an ongoing change in the environment that endangered adaptation and thus represents a stressor (Selye, 1955) that needed to be coped with in an emergency mode. Given this change in the relevant subpopulation, we expected a different probability around the change point τ that a randomly chosen day i will be classified as displaying the aggregate expression j . We further expected around the highest likelihood of that change point τ a relevant exogenous event to have taken place, that must have affected the relevant subpopulation. In order to prove this, we programmed the model in python 3.8.9 from scratch, using the following modules: numpy, pandas, scipy, matplotlib, math, sys, os, and random. The code and data examples can be inspected in the OSF repository of this paper.

The first wave of the novel coronavirus represented a clear exogenous shock that permanently changed the contextual embedding of individuals and therefore offered an unique and perfect opportunity to study our hypotheses in an natural experimental setting, assuming a within-subject design. In order to understand effects of this relevant contextual change in an *in vivo* setting without interference through surveys or laboratory settings, we decided to not let subjects take tests or questionnaires, but to deduce latent psychological traits from the text of SNS users. By focusing on text from SNS, we approximated the influence in the information field of societies, which we used as the proxy for changes in the social embedding of individuals. Though, one could argue, that despite individuals influencing each other, SNS users represented a closed group and therefore the self-selection bias (Zhang et al., 2018) represented a hidden between-subject design of those persons exposed to information field on SNS, and those that are not, we argued that the effect of the novel coronavirus is so encompassing and permeates so many aspects of society, that no user can be found that was not influenced by the COVID-19-related information field and therefore represents a natural experiment.

To further approximate the effect of this changed information field on the general public, we refrained from using niche SNS like Reddit or semi-public SNS like Facebook or LinkedIn. Instead, we focused on public Tweets on Twitter, which can be read by every internet user, and which were very often embedded in homepages like news or blogs, thus representing the overall information field. To ensure observing a relevant subpopulation, we filtered out only on those Twitter users, who wrote about COVID-19-related tag-words.

Using computational methods to predict latent psychological traits

Unfortunately, this ideal positioning of Japan limited also our choice of tools for language analysis, since the field of psycholinguistics was in its infancy in Japan. Until today, even a dictionary for LIWC, the quasi-standard for psycholinguistic research, was still in preparation, and researchers used so far a less than ideal approach of translating the Chinese version of LIWC with online translation tools (Guntuku et al., 2019; Shibata et al., 2016). With less than 18% similar words in daily use, and many different linguistic concepts (Ishii and Onuma, 1998), this approach was not up to the standards required for our endeavour. Therefore, we decided to use the commercial version of IBM Watson Personality Insights, which had wide-spread industry coverage, yet had been rather under-utilised for academic purposes.

Also, the first version of IBM Watson Personality Insights was based on LIWC, and had been since then optimised and further developed by IBM internally, using an open dictionary approach, which outperformed their first LIWC-based model, reaching for the Big Five Dimensions in the Japanese language an Mean Absolute Error of 0.1, and an average correlation with survey-based outcomes of 0.3, which was well in the average of psycholinguistic literature that described prediction values based on text between 0.2 and 0.4 (IBM, 2021). Unfortunately, this later model was not very well documented, so we could not explore deeper technical details. However, despite the 'low' correlation, we considered the outcomes of IBM Watson Personality Insights as just an imprecise measurement, and therefore adding to the measurement error ϵ , which should be reflected in the stationary fluctuation of the state value s around the real latent trait z and its emergency expression z_e .

The advantage of using predictive approaches for measuring latent psychological traits *in vivo* and in a non-invasive way came at various expenses. First, we only could provide assumptions of causality, since no grounding through behavioural

surveys or observations took place. Second, we neither could control the contextual conditions under which the SNS texts were created, nor sort individuals by their specific life situations that influenced them at that point in time. While extreme exogenous events were equally influential for most people, some may face other, more relevant situations like personal tragedies. This would increase the measurement error for these persons disproportionately. Third, individuals were influenced by media events and their relevant social networks. Since SNS were by definition social networks, in which media and news were distributed, we assumed mutual influence of its users, which further weakened our ability to infer causality from observations on an individual level. Last, resulting from these points, we assumed that the i.i.d. assumptions were violated, and with that the normality assumption, as well. While we expected this effect to be less strong with clusters of individuals under mutual influence in the same context, it would be prevalent with randomly chosen SNS users. This reduced both the choice of sampling, as well as that of methods.

We concluded that an analytical strategy on an individual level would be way too 'noisy', and that the effects of extreme exogenous conditions on personality should be observed in patterns of larger samples of individuals, clustered by similar psychological properties. The five factor model was a prime candidate for that, since it was well established in psychology, had been used in a variety of adjacent fields, and various methods to measure it have been developed, from the predictor (Ortner and Schmitt, 2014), over the criterion (Ones and Viswesvaran, 2001), to the outcome space (Gosling et al., 2002). While it would be preferable to generate these clusters based on a more profound theory of personality types, these were a rather difficult topic, with a variety of rather controversial opinions and research approaches. The most agreed-upon approach seemed to be conducting latent class analyses, mixed Rasch models, or the SEM approach from Raykov (Raykov et al., 2020). However, since our research was based on a survey-free *in vivo* approach, most underlying assumptions would be violated. Mainly when using a maximum likelihood estimation, we would have struggled with independently and normally distributed residuals (Curran, 2003) given the considerations above.

Since we explored the influence of the information field of extreme exogenous conditions on personality of clusters of people, and since we measured within-subject variance, yet assume mutual and contextual influence, we therefore decided to cluster individuals by the baseline of their past FFM-expression. While theoretical, the distribution of the expression of FFM was assumed to be normally distributed, we could not expect this to be the case in a sample that was chosen by usage of tag-words from SNS, which already came with a self-selection bias. Also, since psychological phenomena displayed a geographic distribution (Rentfrow et al., 2008), and since we expected a larger portion of the users to be from urban centres, we assumed a skew in distribution. Hence, we created baselines of users based on the interquartile distance, focusing on the top 25% users of each expression of the FFM in 2019, the year before the outbreak. This clustering resulted individuals belonging to one (O,C,E,A,or N) or several (for example, E/A) top groups per FFM dimension. To capture the pure effects per FFM dimension, we decided to only focus on those individuals belonging to only one top group, ignoring the mixed types.

Next, we clustered the Tweets from each of the top OCEAN groups on a daily basis, and derived personality measures from that, using IBM Watson Personality Insights, and brought these into a time series, displaying the change in personality expression per cluster. That means that for each top OCEAN group from before the outbreak, we derived OCEAN expressions from after the outbreak, resulting in 25 time series.

Figure 1. FFM Prediction Approach

To finally evaluate whether a change took place, we first inspected the time series visually, and then tested on stationarity

via autocorrelation and autoregression using pandas, statsmodels, math, and sklearn for Python. Then, we conducted the Bayesian regime-shift analysis to those time series, where we found significant changes, using numpy, pandas, scipy, and math for Python. Since the Bayesian analysis already distinguished between probabilities of belonging to different distributions, we refrained from conducting additional confirmatory t-tests between the distributions separated by the regime-shift points. Finally, to identify whether a change in the information-field took place that was concordant with the regime-shift in personality, we analysed Tweets during the identified periods before, between, and after the points of regime-shift by wordclouds and structured topic models (STM). We generated the wordclouds with quanteda in R and Mecab for a morphological analysis in Python, and the STM with the stm package in R.

We applied the above model of a potential personality regime shift in the following way: $x_i = j$ stands for an label x that a day i had the expression j of a relevant measured aggregate psychological latent trait. We had n days, and k potential expressions of that aggregate psychological latent trait. Those measurements took place m times, thus $(t_1, \dots, t_m)$ representing m time intervals, in which for every day i , the very same aggregated psychological measure was generated.

3.1. Data

For the analysis, we collected the following data, of which we will subsequently give a brief description:

1. Relevant Tweets from Japanese Twitter users
2. Timeline of events
3. Official Corona Numbers

3.1.1. RELEVANT TWEETS FROM JAPANESE TWITTER USERS

A sample from Japanese Twitter users bore four major advantages. First, Japan was close to the origin of the novel coronavirus in Wuhan, China, and there was a historic close relationship between the two countries, including a significant Chinese population with close ties to China. This made Japan a prime country for being hit by coronavirus effects first, before other countries. Second, given it's otherwise rather secluded geographic location as an island nation, with traditionally rather closed borders and low degrees of English skills in the population, we assumed the effects on the population to be more free from outside interference in the information field, which transformed it into a quasi laboratory for our purposes. Third, Japan had the second largest user base after the USA, more than double the amount than the next biggest user base, India. The 50.9 Million Japanese users made Twitter a significant SNS in Japan, with about 40.6% of the Japanese population using it. This made it more representative than using it for example in the USA, where 69.3 Million people used this service, or about 21% of the population (Tankovska, 2021). Last, there was a distinct event that initiated the virus in Japan, with the arrival of the cruise ship Diamond Princess, and therewith, we could identify a perfect starting point for our model.

We collected the recent 3,200 Tweets from all Japanese Twitter users, who 'tweeted' between January and June 2020 about the following COVID-19-related keywords: 'Corona', 'COVID', 'Pandemic', 'Face Mask', 'Hand Sanitizer', 'Hand Soap', 'Toilet Paper', 'Napkins', and 'Tissues'. We selected all hygiene-related keywords, since soon after the outbreak, many of these articles were sold-out in stores and thus a relationship with the keywords and COVID-19 is obvious. Also, this allowed us to capture a broader range of the phenomena over and above purely COVID-19-related Tweets.

For some users, these 3,200 Tweets represented their life-time Tweets, for others only the last couple of years or even months. The number was based on the restrictions from the official Twitter API that we used. To communicate with it, we used Python with the following packages: numpy, pandas, tweepy, datetime, and pytz.

This resulted in 7,435 Twitter users and 23,501,189 Tweets, whereby some only 'tweeted' about one or two, others about all topics. The average user produced 3,160.89 Tweets. Unfortunately, we could not derive any demographic information due to API restrictions, and missing official statistics from Twitter. However, given the importance of Twitter in the Japanese SNS market, we assumed the sample to be representative of Japanese society.

3.1.2. TIMELINE OF EVENTS

To capture on the ground truth, we manually created an extended timeline of COVID-19-related events from December 2019 to June 2020. The reason for choosing this time span was that the novel coronavirus was reported for the first time

between December 27th and 29th 2019 from various local hospitals in Wuhan, China, to the local branch of the Chinese Center for Disease Control and Prevention. A day later, it was discussed in groups from Chinese social networks for relevant medical personnel, and appeared on international Flu tracking websites, just to be officially reported to the World Health Organisation the next day, on December 31st, 2019. From there, first reports spread to Japan early January, as discussed later. We chose June 2020 as an end-point, since that is when the number of hospitalisations in Japan was significantly reduced, and some countries announced the end of the first wave (Tashiro and Shaw, 2020).

To generate an exact time-line of the events, we manually searched several sources for COVID-19-related events, including news, official governmental announcements, coverage from international bodies like the UN and WHO, as well as from various NGO. This choice of sources is based on both availability of information and the need to understand the contextual embedding of Japanese Twitter users when they are exposed to information. Findings from media psychology indicate that those news have the highest values to individuals that are negative and of geographic proximity (Araujo and van der Meer, 2020). However, systems theory indicates that also more distal events may have an influence on a local level if those are within the broader systemic context (Willke, 2000). Therefore, we theorised a layered model of relevance for individuals, whereby more proximal events had a stronger relevance than more distal ones, for example announcements from the Japanese government should have been more influential than those from the World Health Organisation. We assumed though, that the latter may still had an influence on individuals, either to a lower magnitude or time-delayed. This resulted in a time-line of daily events in that period, with varying levels of local importance that allowed us to establish a solid understanding of on-the-ground-truth. We used that timeline to identify what exactly happened at the day of the regime shift. A complete chronology of the events in Japan, the geographic importance to Japanese Twitter users, and the respective sources can be found in the OSF Repository.

3.1.3. OFFICIAL CORONA NUMBERS

For further understanding of this on-the-ground-truth, and for quantifying real-life events, we used the official numbers provided by the Japanese government (MHLW, 2021), which we cross-checked with data from the World Health Organisation (WHO, 2021) to ensure their correctness. We used these numbers to augment the qualitative time-line of daily events by quantitative measures and to visualise the development of personality change in contrast to real-life effects of COVID-19-related like hospitalisations and deaths.

4. Results

We conducted the analyses in alignment with the lead logic to first extract daily personality measures, then identify potential patterns in those, and analyse whether the emergence of these patterns aligned with external events that either act as exogenous shocks or change the contextual embedding of Twitter users, which made them adapt and communicate in an emergency mode. To add additional evidence, we further analysed the content of Tweets in the relevant times before patterns emerged. For this, we conducted the following steps:

1. Language-based Personality Predictions
2. Tests for Stationarity
3. Bayesian Analysis
4. Timeline of Events
5. Text and Topic Analysis on Tweets

4.1. Language-based Personality Predictions

IBM Watson Personality Insights delivered results from the FFM in percentile scores, which we generated for each of the five top 25% FFM groups on a daily basis. We then brought these into a time series that covered the onset of the COVID-19 pandemic on the 29th of December, 2019, until the end of the first wave on the 15th of June, 2020. All time series of the five groups were depicted and described in the appendices. The most promising group to display changes in personality seemed to be the top 25% Conscientiousness from 2019, which displayed a distinct change in Extraversion and Agreeableness, and maybe in Neuroticism, as well. While Extraversion was most interesting, since it changed order with Neuroticism,

Agreeableness seemed to display the most distinct regime-shift, and Extraversion seemed to have a broader range in general, wherefore we decided to conduct further analyses with Agreeableness.²

Figure 2. Extraversion and Agreeableness vs Hospitalisations and Deaths

Figure 2 shows an overlay of both the time series of Agreeableness and Extraversion of the top 25% Conscientiousness group from 2019 with the time series of the official COVID-19-related deaths and hospitalisations. It shows that these peak during the regime-shift, which seemed to start around the first inflexion point of Hospitalisations. The FFM percentiles were plotted on the ordinate and the date on the abscissa. The authors concluded that there is enough evidence to conduct further analyses as planned.

4.2. Tests for Stationarity

We tested for stationarity by autocorrelation and autoregression. As expected, the autocorrelation function (ACF) plot for Neuroticism indicated stationarity. It degraded with increasing lag quickly to zero and fluctuated around it. However, aligned with prior expectations, the ACF plot for Extraversion indicated non-stationarity and thus indicated that a regime-shift took place. Also, the ACF plot for Agreeableness indicated non-stationarity and thus indicated that a regime-shift took place, as well. In summary, Extraversion and Agreeableness displayed non-stationarity and were candidates for further analyses. These results were further confirmed with an autoregression model, creating a seven day forecast with a lag of 29 days. Extraversion (RMSE: 2.515) performed worse than Agreeableness (RMSE: 1.343). Therefore, aligned with visual inspection, the Bayesian Analysis to determine the point of regime-shift was conducted using the Agreeableness time-series from the 2019 top 25% Conscientiousness group.

4.3. Bayesian Analysis

To determine the point of regime-shift, the model from section 2.2 was implemented in Python on the Agreeableness time series displayed in figure 3 in grey. The resulting updated posterior distribution represented the probability for a regime-shift for each day that could have been caused by the COVID-19 pandemic, and was calculated using Equation 16. It is plotted in figure 3.

²An interesting side-finding, which could be explored in future publications was that each group displays a different order in the strength of FFM factors, as well as a different overall range in their expression.

Figure 3. Time series of Agreeableness vs Probability of Regime-Shift

Counter-intuitively, and against prior assumptions, this posterior plot indicated two (plus one) plausible candidates of regime-shift in the data, whereby the first point was the most likely, and was preceded by a smaller burst. The first distinct point of regime-shift took place at day 58, which was the 24th of February 24, 2020, and it represented a probability of 36% that the regime-shift took place at that day. It was preceded by a smaller burst on day 54, which was the 21st of February, 2020, and it represented a probability of 6% that the regime-shift took place at that day. The second spike was at day 86, which was the 25th of March 25, 2020, and it represented a 3% probability that the regime-shift took place at that day. However, since the posterior distribution represented the probability of a regime-shift, the first distinct point was most important for interpreting the outcomes. Given the probabilistic nature of human behaviour though, we treated each point as a potential regime-shift in the interpretation.

4.4. Results from Timeline Of Events

For this, we created a timeline of daily COVID-19-related events to understand, which exogenous event took place around the regime-shift points of personality change. In line with various theories on relevance of geospatial embedding, we included such from international bodies like WHO, more distal areas like the EU and US, more proximal areas like China, and from Japan. The full timeline can be viewed in our OSF repository.

The 'real' point of regime-shift then occurred on 24th of February, 2020. At that day, an official expert meeting for the novel coronavirus took place in Japan, in officials from the Ministry of Health, Labour and Welfare discussed ways to contain group infections, secure hospital beds and help people acquiring better understanding about the virus. A day later, that same ministry established a Cluster Response Section in accordance to the Basic Policies for Novel coronavirus Disease Control, which was decided upon the same day by the newly formed Headquarters for Novel coronavirus Disease Control of the Japanese government and announced by prime minister Abe Shinzo to the public. Finally, he announced just two days later, on 27th of February, 2020, that all schools in Japan would be told to close until April to respond to the outbreak.

The burst before the 'real' point of regime-shift occurred on 21st of February, 2020. At that day, the organisers of the Nagoya Women's Marathon cancelled participation for the public and only allowed elite athletes to participate amid fear of increased infection in crowds. Also, the Paralympics Boccia tournament was postponed to protect athletes. A couple of days earlier, on the 17th of February, 2020, the Ministry of Health, Labour and Welfare presented for the first time guidelines on seeking medical help in case of COVID-19 infection. This was interpreted as a 'pre-activation' of the public awareness of real-life ramifications of COVID-19 in mass events, which then was 'activated' for the first time on the 21st of February, 2020, where the said decisions were made. We further assumed a pre-existing 'pre-activation' of public awareness of everything related mass-sports-events, since Japan was preparing for the 2020 Olympics that were planned to take place in Tokyo.

The second point of regime-shift took place on March 25th, when the governor of the Tokyo Metropolitan Government Koike Yuriko urged residents to stay at home during weekends, just a day after prime minister Abe Shinzo and the International

Olympic Committee (IOC) announced the Tokyo 2020 Olympics to be postponed to 2021 amid the uncertainties of the pandemic.

The two points of regime-shift had in common that these occurred around official announcements from the government, surrounded by announcements from the Olympics, concerning mass-events. Since Japan had been preparing for the Olympics, and since these were heavily advertised in Japan, involving many parts of the population, the relevance was greater for the population than other events. Also, Japan was known for its conservative culture and high trust in the government (Kim and Voorhees, 2011), so again, official announcements from the government were relevant for Japanese people. In line with the theory outlined earlier, negative and spatially proximal news were more relevant in public perception.

It is therefore a good explanation that in the uncertain and fear-loaded atmosphere during the onset of the COVID-19 pandemic, the official announcements from the IOC and the prime minister led to the perceived personality changes. Especially the high conscientiousness group might have been receptive to messages from authorities, since rule-obedience is highly correlated with (Bègue et al., 2015). Furthermore, the displayed significant increase of agreeableness and extraversion was aligned with findings that humans cooperate more strongly in situations of adversary and danger (von Dawans et al., 2012-06-01), for which it was helpful to be more nice to others (agreeableness) and to reach out to them in the first place (extraversion). The slight increase in neuroticism, that was also reported by other studies (Sutin et al., 2020) was not significant, which makes sense, since in emergency situations, it was relevant to have higher degrees of emotional stability as an emergency expression z_e of ones latent traits z .

4.5. Results from Text and Topic Analysis On Tweets

To understand what Japanese Twitter users were talking about in the respective time slots between the regime-shifts, and to better understand whether COVID-19 or other, more seasonal topics dominated, we conducted quantitative content analyses of the Tweets from the top 25% group of high Conscientiousness, on which the analysis on regime-shift points was based.

First, we divided the paper into six periods, which are listed in table 1. All Tweets on and before 31st of October, 2019, formed a baseline for overall understanding of what the top 25% Conscientiousness group was talking about. To better understand the influence of the pre-holiday and holiday season on Tweets, we created the next period on and between 1st of November, 2019, and 28th of December, 2019 – the day before the outbreak. For the time from the official outbreak towards the first burst before the actual point of regime shift, we created a time period on and between the 29th of December, 2019, and 20th of February, 2020. This time span described the most interesting part of psychological change, where fear of the unknown was more present than actual, scientifically-proven facts. The time on and between this first burst and the actual point of regime shift, was on and between the 21st of February, 2020, and 24th of February 2020. Though being a small time-span, we included it to understand what users 'tweeted' about between both official events described before, when COVID-19 got increasingly more influence on their lives. We further included it to test, whether both events are separable or whether we should consider them as one big event of regime shift. To better understand what users spoke about between the actual first and second point of regime shift, we included the time on and between 25th of February, 2020, and 23rd of March, 2020. And finally, to understand what users 'tweeted' about after the second point of regime-shift, we took the time on 24th of March, 2020, and thereafter.

Personality Change During Extreme Exogenous Conditions

Period	Description	Number of tweets
$-\infty$ - 31.10.2019	baseline in general (included to get an overall understanding of what people are talking about)	277,348
01.11.2019-28.12.2019	pre-holiday season (included to understand influence of period shortly before outbreak)	111,392
29.12.2019-20.02.2020	outbreak until first regime shift (included to understand short burst before actual first point)	128,300
21.02.2020-24.02.2020	short burst to first regime shift (included to understand whether short burst is different to actual first point of regime shift)	9,753
25.02.2020-23.03.2020	first regime shift to second regime shift (included to understand what happened before second point of regime shift)	75,889
24.03.2020- ∞	after second regime shift (included to understand what happened after second point of regime shift)	240,853

Table 1. time span and the number of tweets for each period

Second, we pre-processed that text data from each period by removing standard stop words that were listed in stopwords-iso Japanese, Twitter-specific stop words (“retweet”, “RT”, “tweet”, “post”, “follow”, and “https”), numbers, and words that are related a retweet contests (“apply”, “campaign”, “retweet contests”, “present”, and “win a retweet contest”) that took place at the time of data collection. We removed Hiragana because it was mainly used for postpositional particles in Japanese texts and therefore did not provide additional meaning for analysing topics (Catalinac and Watanabe, 2019). The pre-processing was conducted partly manually, partly with the quanteda subpackage for stopwords (Benoit et al., 2018) – using R, and the International Components for Unicode (ICU) dictionary for tokenisation. For the sake of an English publication, we translated all text with the DeepL, using its API for R. Furthermore, we eliminated information about word order in the resulting corpora since the wordcloud and the Structured Topic Model (STM) we used in the next steps were based on bag-of-words design.

Third, we analysed what Twitter users ‘tweeted’ about in each period using wordclouds, which was based on simple calculation of word frequencies from a random sample of 4,000 words in each corpus to control against sample size bias and reduce computational complexity. We restricted those wordclouds to the top 150 words, to make them more readable. Since wordclouds represented text content in this shallow way, the before-mentioned pre-processing helped extracting more meaning from them. For generating the wordclouds themselves, we used the quanteda textplots package in R. We then manually analysed and interpreted the content of each wordcloud. Those wordclouds are depicted in our OSF repository. People ‘tweeted’ increasingly about COVID-19-related topics, and the restrictions for daily life, that came with it. Words

indicative of lifestyle, fun, and music faded, whereas survival and emergency-related words emerged, indicating that the population entered an emergency mode. As discussed before, this maybe was indicative that the most conscientious people focused increasingly on cooperation against an outer threat, which demands extraversion and agreeableness. In line with that hypothesis, it was indicative that People used more often Katakana terms such as 'COVID-19', 'masks', and 'news'. It is used for both technical terms, but also for non-Japanese words, indicating that the virus was associated with something hostile that came from abroad. This led the authors to the conclusion that the points of regime-shift indicated clear shifts in both narrative and displayed personality, based on extreme exogenous conditions.

Fourth, we analysed the pre-processed Tweets, merging-together all periods into one clean corpus for creating a STM, which is the more progressed version of a Latent Dirichlet Allocation (LDA). The goal behind this step was to better understand what topics were discussed and how these topics developed over time, capturing higher dimensionality of text than wordclouds can do. For this, we used the stm package in R (Roberts et al., 2019). Previous studies (Blei and Lafferty, 2009; Griffiths and Steyvers, 2004) pointed out that the results of STM analyses were variable when the number of topics was changed. Therefore, we used the searchK algorithm from the stm package to determine the optimum number of topics, which was 28 for the subsequent analysis. The detailed outcomes of this analysis are depicted in our OSF repository.

Overlapping with the results from the wordclouds, lifestyle topics dominated, one economic/ everyday life issues topic was constantly present, and so was one COVID-19-related topic. This mainly covered the pandemic itself, the restrictions it brought to the daily lives of people, as well as the resilience those evoked, forcing them to switch to a survival or endurance-mode. Interestingly, no topics covered the Olympics, nor holiday-related aspects, nor the government.

To further understand how the proportion of topics changed over time, we plotted the expected topic proportion of two select topics over the six periods from table 1: the COVID-19-related topic, and the topic that covers economic/ everyday concerns. Also, while the COVID-19-related topic was represented in the wordclouds as well, the topic covering commercial/ everyday concerns only became visible in the stm, which indicates that it is representative of 'baseline' of everyday life, and therefore is a good comparison to the emerging topic from the pandemic.

Figure 4. Change in topic estimation by STM

Figure 4 confirms that the proportion of the COVID-19-related topic 19 increased steadily over all six periods, whereas the 'baseline' economic topic 12 remained constant – no matter whether the government requested the citizens to stay at home and shorten the business hours, phases of states of emergency, or 'free' periods in between. We assumed that this was because COVID-19 was such an important issue that permeated all life spaces, and brought so many restrictions and risks, that it was hard to avoid. In summary, as compared to 'baseline' topics, COVID-19-related topics became over time more all-encompassing, intangible, yet permeating all areas of life.

5. Discussion, Limitations, and Future Directions

Since we only observed this significance in changes in Agreeableness and Extraversion in the sub-group of top 25% Conscientiousness, while Neuroticism was not significant, we presumably either captured cultural, sampling, measurement,

or methodological effects. Studies from the United States of America found Extraversion to go up, as well, but also a significant rise in Conscientiousness and Neuroticism, while Agreeableness and Openness decreased (Ahmed et al., 2020). On the other hand, Sutin et al. (2020) just found a slight decrease in Neuroticism, while other FFM factors displayed no significant change. An explanation for these differences maybe was a sampling effect. We focused on the top 25% users who 'tweeted' about COVID-19-related issues, while Sutin et al. (2020) used a stratified sample, and (Ahmed et al., 2020) focused on health workers - a group that showed also in other cultures a higher vulnerability due to stronger exposure to pandemic-related events (Sugaya et al., 2020).

Another explanation for varying outcomes in different studies could have been the timing and circumstances of measurement, which indicated different levels of reliability and thereby, generalisability. Ahmed et al. (2020) focused on the time of February to April 2020, whereby they captured everything that happened before and during the first wave of COVID-19. That means that they most certainly have artefacts from seasonality and other exogenous events in their results, as well. So did Sutin et al. (2020), who focused on February and March, whereby we did not know about the circumstances under which the tests were taken. Our time-series approach de-cluttered these effects, and gave – for the first time – insights into daily changes, providing better understanding on the importance of timing of test-taking. However, this came with the cost of ignoring within-person results, since we aggregated daily results.

Additionally, we may have captured effects from language models that were trained on general data, and not data from extreme events, wherefore the classification of the predicted FFM factors might have been wrong. This would also explain the extreme results in the Ahmed et al. (2020) study, whereby Sutin et al. (2020) found rather moderate changes - but they found changes, which indicates that the notion of slowly personality traits needs to be put to further scrutiny and research.

Furthermore, the deployment of IBM Watson Personality Insights as a tool for research comes with a number of limitations. First, though its origins are in LIWC and the original model used word embedding features with Gaussian Process regression (Ahmed et al., 2020), the current version seemed to be a black box, and no technical details but of some vague prediction performance parameters were published in the technical manual (IBM, 2021). For example, it is not clear whether the English model was just translated, or whether a new model for each language was created. Most importantly though, the results cannot be replicated since the service was deprecated by end of 2021.

A follow-up study should overcome these problems by deploying the same technique just with different cultures, and, if possible, user groups. Also, further analyses should be conducted that understand the change of topics and emotions over time, making use of more rich text features, for example emoticons and emojis. Also, grounding studies should be conducted that involve self-reported surveys, geospatial data, or identifiable point of sales activities like purchases. Also, new sources of text would be helpful, for example emails or journals. Lastly, a different personality prediction model should be used that does not depend on IBM Watson Personality Insights nor on any other commercial service that can be deprecated any time.

Finally, our methodology was novel, but not state of the art. We suggest follow-up studies that involve either Deep Learning, Hidden Markov Models, or Monte Carlo techniques for Bayesian Analytics to make use of more data and capture effects that weren't obvious from our current approach. Also, different language models for feature extraction should be deployed, maybe trained anew based on times with and without extreme exogenous conditions, to better control against these conditions.

6. Conclusion

We introduced a new methodology of time series measurements to personality research, focusing on daily measurements and deploying methodologies from adjacent fields that haven't been deployed to this extend in psychometrics. By using Bayesian analytics, we further created a new approach to identify points of regime-shift within this context.

Results from this methodology indicated that personality measures changed under extreme exogenous conditions during the first wave of COVID-19 and the subsequent societal countermeasures. We interpreted this change in latent psychological traits as a shift from the normal expression z to the emergency expression z_e , which seemed to be temporary, and indicated that personality displayed a degree of elasticity, which goes over and beyond the reported slower changes over a life-type or state/ trait differences, which were partly subject to measurement variance. On a behavioural level, this change in personality can be interpreted as a social signalling and coordination process, as well as a pre-activation for future behavioural changes that are necessary for survival.

If future studies displayed similar results, the idea of state personality expressions might have to be extended as a dynamic

function of elasticity, or the ability and function of personality to adaptively regulate perception and behaviours based on contextual embedding. This would be concordant with newer findings from biology that show that DNA displays both slow changes over time (Gorbunova et al., 2007), as well as quicker changes in form of deployment of more genetic potential (Meyers et al., 2005), depending on outer circumstances.

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