Coping with Corona (CoCo): Understanding individual differences in well-being during the COVID-19 pandemic

Project Description

1 Starting point
The COVID-19 pandemic poses major threats not only to people’s physical health but also to their psychological well-being (Diener et al., 1999). People are encouraged to physically distance themselves from others and restrict their everyday social choices, while simultaneously dealing with unpredictable developments. Importantly, people differ in how they cope with these challenges. Recognizing these differences is key to understanding how the Corona crisis (and similar health crises) works psychologically and is critical to developing personalized interventions. The present interdisciplinary and multi-methodological project aims to predict and understand individual differences in Coping with Corona (CoCo).

1.1 State of the art and preliminary work

Individual differences in well-being during the COVID-19 pandemic
Many studies have examined general mental health issues during the COVID-19 pandemic (e.g., Rajkumar, 2020; Thombs et al., 2020), and reported either decreases in well-being (Zacher & Rudolph, 2020) or no change (Entringer & Kröger, 2020). Importantly, such general effects hide individual differences in how people cope with crises. Existing studies that included individual difference variables have focused on sociodemographics (e.g., Lai et al., 2020; Sun, Balabanova, et al., 2020; Wang et al., 2020). Far fewer studies have examined the effects of personality traits (Aschwanden et al., 2020; Kroencke et al., 2020; Modersitzki et al., 2020; Zettler et al., 2020), which is surprising because personality is a particularly robust predictor of well-being (Costa & McCrae, 1980; DeNeve & Cooper, 1998; Eid & Diener, 1999; Soto, 2019; Steel et al., 2008): Extraversion, agreeableness, and conscientiousness are typically linked to higher well-being, whereas neuroticism predicts lower well-being. These differences are likely to be pronounced during environmental challenges characterized by novelty, uncertainty, and unpredictability (Caspi & Moffitt, 1993), such as those experienced during the COVID-19 pandemic.

Social interaction processes
Despite initial insights on predictors of well-being during the COVID-19 pandemic, there is almost no research on which social processes explain these individual differences. The environmental challenges involved can be expected to trigger differences in how individuals socially deal with the pandemic. These differences in social interaction processes (see Back, in press) need to be considered to understand why some people suffer, while others stay comparatively happy or even thrive during the crisis. Here we focus on three key domains of social interaction processes: (a) social situation selection (in how many and what social interactions people engage in), (b) interpersonal perception (how people perceive others within social interactions), and (c) emotional co-regulation (e.g., how interaction partners support and mimic each other’s coping efforts).

Social situation selection
Every day, people make choices that shape the quality of their social lives. This includes the quantity and quality of social interactions in which they engage (Sun, Harris et al., 2020), the types of relationships they maintain (Hudson et al., 2020), and the communication channels they prefer (Harari et al., 2020). The COVID-19 pandemic has transformed characteristic features of social life, for example by reducing in-person and increasing computer-mediated interaction. This is consequential because the choice of social situations is related to both well-being and personality.
Interactions with close ties (vs. weak ties; Venaglia & Lemay, 2017) and with friends (vs. family; Mueller et al., 2019) as well as face-to-face interactions (vs. computer-mediated interactions; Kraut, et al., 1998; but see Valkenburg & Peter, 2007) are typically associated with higher well-being. Personality is related to both, the choice of social situations (people higher in extraversion tend to socialize more, both in-person and online; e.g., Asendorpf & Wilpers, 1998; Gosling et al., 2011; Harari et al., 2020) and the degree to which different choices foster well-being (e.g., people lower on extraversion profit more from computer-mediated communication, van Zalk et al., 2011; e.g., people higher in neuroticism profit more from interactions with friends, Mueller et al., 2019). How such interactions will play out in the context of a global pandemic is unclear. We expect that people more strongly differ in how they choose among remaining social situations and how well they adjust emotionally to the restricted set of choices. Personality should show both, stronger main effects on situation selection and more pronounced moderation of situation selection effects on well-being; thus, leading to a stronger influence of personality on well-being during the COVID-19 crisis (see p. 11 Top-down hypothesis testing for an initial overview of derived hypotheses).

Interpersonal perception
During interactions people continuously observe and perceive their social partners to guide their own behavior and social decisions (Kenny, 2020; Nestler & Back, 2013). Three interpersonal perception processes are particularly consequential: (1) generalized other processes (how positively people perceive others; e.g., Rau, Carlson et al., 2020), (2) sociometer processes (how much people think they are accepted and liked; Leary & Baumeister, 2000), and (3) shared reality processes (how much people perceive to share the same thoughts and feelings about the world around them; Echterhoff et al., 2009; Rossignac-Milon et al., 2020). All of these processes are challenged during a pandemic that is characterized by unclear social rules, unpredictable behaviors of others, and uncertainty about how others feel about the pandemic and ways to counteract it. Again, this is important because differences in interpersonal perception are linked to well-being and personality. People who believe that others have positive characteristics, who perceive themselves to be accepted, and who think they have a shared understanding of the world tend to be happier (e.g., Reitz et al., 2016). With regard to personality, agreeableness relates to more positive perceptions of others (e.g., Rau, Nestler, et al., 2020) and neuroticism relates to more negative perceptions of how one is viewed by others (e.g., Back, Schmukle, et al. 2011). No data exists on the role of interpersonal perception processes in the wake of a pandemic. We expect pronounced individual differences in and personality effects on interpersonal perception processes and their effects on well-being (see p. 11 Top-down hypothesis testing).

Emotional co-regulation
Emotional co-regulation (“dyadic processes that maintain and increase emotional stability between social interaction partners”; Butler & Randall, 2012; p. 204), includes (1) support (e.g., expression of empathy/warmth and instrumental aid) and (2) mimicry (e.g., mimicking negative and positive affect). Given increased stress levels and need for social validation, these dyadic processes should be particularly relevant during the COVID-19 pandemic (Saltzman, et al., 2020), and they are both related to well-being and personality. Support generally buffers against detrimental effects of stress on well-being. Co-rumination refers to a dysfunctional mimicry process, whereby social partners increase each other’s negative affect, even when perceptions of support are high (Rose, 2002). Prior studies (Horn & Maercker, 2016; van Zalk, et al., 2010) show that a joint passive and rigid repetitive focus on negative affect (co-brooding) is especially dysfunctional. While it leads to feelings of being understood, it also decreases beneficial effects of partners’ support on well-being (van Zalk, et al., 2010). Co-reappraisal refers to the sharing of
positive emotional affect, with the goals of shared clarification, dyadic cognitive restructuring, and jointly finding meaning, which enhances beneficial effects of partners’ support on well-being. How these co-regulation processes affect well-being may depend, however, on the partners’ personality. Social partners high in neuroticism, for example, might be more susceptible to negative emotional contagion (e.g., Mueller, et al., 2020). We expect that during the pandemic, individual differences in the tendency to engage in and the susceptibility to effects of co-brooding and co-reappraisal on well-being will be pronounced (see p. 11 Top-down hypothesis testing).

Preliminary own work

The CoCo project will rely on interdisciplinary expertise of leading experts in the fields of personality, relationship, behavior, developmental, network, and data science. Data collection and analysis tools involve experience-sampling methodology (ESM; i.e., repeated reports on people’s thoughts, feelings, and behaviors during their everyday life) and mobile sensing techniques (i.e., the continuous passive sensing of objective situational and behavioral features in people’s everyday life), predictive modeling/machine-learning algorithms, multilevel structural equation modeling, and dynamic network models. The applicants and international collaborators (Prof. Gosling, Prof. Harari, Prof. Matz; see 6.5) have run studies and pretested relevant procedures and materials in the context of the current crisis and have an extensive history of collaboration.

Prof. Back investigates the interplay of personality and social relationships with a focus on mediating interaction processes. His work includes theoretical (see Back, in press; Back, Baumert et al., 2011; Geukes et al., 2018) as well as empirical research on the co-development of personality and peer relations (e.g., Hutteman et al., 2015; van Zalk et al., 2020), predictors and consequences of interpersonal perceptions (e.g., Human et al., 2020), and the variable expression of personality across situational contexts (e.g., Geukes et al., 2017). His integrative methodological approach covers cross-sectional and longitudinal, correlational and experimental designs, and self- and other-reported, and behavioral data (Geukes et al., 2019; Mahmoodi et al., 2017). Since March 2020, his team has set up 3 large ESM studies that cover the first lockdown phase, and analyzed personality predictors of COVID-19 related evaluations and attitudes (e.g., Zettler et al., 2020), and of everyday behaviors and experiences (e.g., Kroencke et al., 2020).

Prof. Bühner is specialized in psychological assessment and methods including mobile sensing, construction of rating scales, factor analysis, and interindividual differences in cognitive functions. His research focuses on the prediction of personality using passive and active mobile sensing (e.g., Harari et al., 2020; Stachl et al., 2017, 2020). Additionally, he investigates general rules for item construction and optimizes problems of factor analysis such as model diagnostics and factor extraction with machine-learning techniques. His team has set up large-scale sensing studies to compare objective social behaviors and situational choices before and during COVID-19.

Prof. van Zalk specializes in social processes that underlie well-being and mental health (van Zalk, et al., 2010), intergroup attitudes (van Zalk, et al., 2013), personality (van Zalk, et al., 2020), and social development (van Zalk, 2011). He has developed and empirically tested theoretical models on the cognitive and socio-emotional mechanisms that explain socialization in everyday interactions between adolescents and their parents, peers, and teachers. By gaining large competitive grants from national and EU agencies, he coordinated international projects in which observational, hormonal, experimental, mobile sensing, and ESM data were collected. He has jointly developed advanced statistical methodology with statistical experts in Social Sciences (for a review see Veenstra, et al., 2013) and applied these approaches to examine individual differences in daily interactions, co-regulation, and well-being in social networks. He collaborates with the Robert Koch Institute and the Prevention Council of Niedersachsen to implement respective community network studies in 14 different countries during and after COVID-19.
1.2 Project-related publications
1.2.1 Articles published by outlets with scientific quality assurance, book publications, and works accepted for publication but not yet published.


2 Objectives and work programme
2.1 Anticipated total duration of the project
36 months (starting date: 01-04-2021)

2.2 Objectives
The CoCo project focuses on individual differences in coping with Corona (see Figure 1). These individual differences are crucial not only for the current crisis but they also need to be understood to deal with similar health crises in the future. Given the lack of basic descriptive data, theoretical models, and predictive insights, and the urgent need for empirically derived applications, CoCo will provide an accelerated scientific cycle involving a comprehensive description (Work Package 1, WP1: CoCo Exploration and Prediction), and explanation (WP2: CoCo Understanding and Targeting) of individual differences in coping with Corona. The key distal outcome is well-being (e.g., Diener et al., 1999), broadly conceived. This includes cognitive components (e.g., life satisfaction, authenticity, meaning in life), positive and negative affective components (e.g., happiness, anxiety, worry), and socially-anchored cognitive-affective experiences (e.g., social connectedness vs. isolation and loneliness). Results of WP1 provide a comprehensive overview of individual differences in coping with Corona and the first robust insights on the role of personality factors (and the person-environment interplay). Results of WP2 will provide detailed insights into the social interaction process dynamics that underlie these individual differences. Results of both WPs will constitute a sorely needed conceptual and empirical step towards the large-scale availability of personalized tools to foster psychological resilience in individuals, groups, and societies in the wake of major health crises.
2.3 Work programme including proposed research methods

Overview and structure of the work programme
The two WPs consist of tasks that all members of the CoCo team (the three PIs, their work groups, and all international collaborators) manage jointly as well as tasks that are specific for each subproject (SP) (see Table 1 at 7.1.1 for a detailed timetable). WP1 and parts of WP2 can be addressed with data that are available at the time of the project start, enabling us to immediately start with analyses and to present first results shortly after. In light of the unpredictable development of the COVID-19 pandemic and its societal consequences, we have built in several alternative options and back-up solutions regarding new data collection in WP2:

1. The most intensive data collection (including both ESM and mobile sensing modules) will take place at different locations in Germany and the US, allowing to capture psychological reactions during different phases of the ongoing COVID-19 pandemic.
2. The basic ESM module will be applied to participants from a wide range of different countries around the world allowing for an even broader coverage of crisis stages.
3. Even in the most optimistic scenario, an effective vaccine will not be available for the whole population across all examined countries before the end of the new data collection.
4. The focused processes are relevant for both lock-down and relaxation phases of the crisis.
5. Consequences of the crisis on interaction dynamics and well-being are expected to be longer lasting beyond immediate reactions to social restrictions and health threats.
6. We will prepare feedback information for personalized targeting fitting both phases of the crisis and will be able to flexibly apply them in each country.
7. To cover the variety of possible reactions, the sampling strategy involves both (a) groups of young adults in selected locations, and (b) a representative coverage of sociodemographics in the main international samples.
WP1: Exploring and predicting individual differences in coping with Corona

WP1 of the CoCo project constitutes the first comprehensive analysis of individual differences in well-being during the COVID-19 pandemic, providing (a) robust estimates of the amount and predictors of well-being differences across (b) a range of well-being indicators and personality traits, including (c) systematic insights on sociodemographic (e.g., age, gender, education), relationship (e.g., relationship status), and environmental (e.g., living situation, local restrictions, number of infections) moderators. Moving beyond standard meta-analytical techniques, we will follow a mega-analytical approach and collect and analyze raw (participant- in addition to study-level) data. This will include data that the group of applicants and international project partners have gathered as well as openly available datasets (see Included datasets below). The large combined dataset (expected N > 20,000) will be carefully integrated, curated, and made openly available (Wilkinson et al., 2016; also see 5.2 Data handling). The data will be analyzed (see Mega-analyses below) with participant-level meta-analyses (adhering to PRISMA-IPD-guidelines) to explore personality predictors and moderators and with machine-learning analyses to build prediction models and identify the most robust (combination of) predictors.

Included datasets

Inclusion criteria. We will consider all datasets that
1. were assessed during the COVID-19 pandemic using country-specific cut-offs,
2. contain basic regional information (at least: country) and date (at least: month),
3. contain at least one indicator of cognitive well-being (e.g., life satisfaction, meaning in life, authenticity), positive affect (e.g., happiness, enthusiasm), negative affect (e.g., anxiety, worrying), or socially-anchored well-being (e.g., connectedness, loneliness)
4. contain information about participants’ gender and age, and
5. contain at least one further person variable that captures
   a. one of the five major domains of personality: Neuroticism (e.g., depressivity, anxiousness, emotional volatility), Extraversion (e.g., sociability, assertiveness, energy level, optimism), Openness (e.g., intellectual curiosity, creative imagination, progressive attitudes/values), Agreeableness (e.g., compassion, respectfulness, trust, honesty, self-transcendent attitudes/values, “dark” traits), Conscientiousness (organization, productiveness, responsibility, industriousness, self-control, impulsiveness),
   b. or a further sociodemographic characteristic (e.g., education, occupational status),
   c. or structural aspects of social life (e.g., relationship status, living alone).

Available own COVID-19 datasets. Our own datasets provide an excellent starting point as they contain all relevant variables, large sample sizes, and cover different phases around the first and second wave of the COVID-19 pandemic in two countries (Germany and the US). All studies include personality and well-being measures (see https://osf.io/2tzp9/ for codebooks).

- EMOTIONS-CORONA (Münster; completed): general population Germany; Sample 1: mid March, n = 1,609; Sample 2: mid May, n = 907; 14-day ESM with 6 assessments/day; number assessments: S1 = 38,120; S2 = 21,884
- Sensor-based Assessment of Behavioral Lifestyles and Experiences (SABLE; UT Austin; completed): US student sample April-August (n = 225); 3-week ESM with 2 assessments/day; mobile sensing (activity levels, mobility patterns, social behaviors)
- Corona and Societal Challenges (CSC; Osnabrück; ongoing): Sample 1: 3-wave community data (11 German communities, total n = 1,622); Sample 2: 3-wave dyadic data (n = 206); Sample 3: 4-wave monthly social network data + ESM (n = 105)
- Young in Corona Times (Osnabrück, van Zalk is co-PI; ongoing): survey in 14 countries
Identification of openly available datasets. The increasing willingness to share data and to develop norms for open data, is particularly pronounced with regard to COVID-19 related research (Yamada, 2020). This data has, however, not yet been used for a more coordinated investigation that allows for robust insights. Following the selection criteria outlined above, we apply a comprehensive search strategy to include all relevant available datasets. Specifically, we perform a keyword-based literature research to identify (1) published peer-reviewed articles (via suitable databases; e.g., APA Psychinfo, Web of Science, PubMed), and (2) preprints (via preprint servers: e.g., psyarxiv.com, medrxiv.org), consult lists of (3) unpublished COVID-19 related preprints (e.g., Syed, 2020), (4) COVID-19 project-registrations (e.g., tinyurl.com/y5lov39j, tinyurl.com/y5h2e72y, tinyurl.com/y4kyuc2b) and (5) online platforms with open COVID-19 related data (e.g., covid19pulse.usc.edu), and (6) launch open calls to the relevant communities (e.g., APA, EAPP, DGPs, SIPS) to obtain information on still unpublished eligible datasets.

Identification of openly available Pre-COVID-19 data. To allow for additional specificity analyses, we include available datasets, that have been gathered prior to the pandemic or cover both pre-COVID-19 and COVID-19 phases. This includes our own data (e.g., 2018-2019 SABLE waves, n = 1,695; 2104-2018 PhoneStudy waves, n = 624, https://osf.io/kqjhr/; 2019 CSC data; n = 428; subsample 2020 EMOTIONS study) as well as openly available datasets. Selection criteria are (a) the inclusion of relevant variables, (b) a broad coverage of sociodemographic and cultural characteristics, and (c) an assessment close to the Corona outbreak.

Mega-analyses

Screening, Eligibility, Data Acquisition, and Coding. After having identified relevant datasets, duplicated data will be removed and the remaining will be screened based on abstracts and, if further included, full-texts. PIs will be contacted to provide the project’s data. For each dataset six coders will (1) assign each well-being indicator to either cognitive well-being, positive affect, negative affect, or socially-anchored well-being; (2) assign each personality variables to one of the five domains and evaluate their prototypicality, (3) dummy-code sociodemographic and relationship variables, and (4) code date and region. Additional context information (e.g., lock-down phase; local restrictions; [rel.] number of infections) will be retrieved using respective trackers and archival data (e.g., Johns Hopkins University, national institutes such as the Robert-Koch Institute). Correlations/standardized regression coefficients will be coded for a study-level meta-analysis; unstandardized regression coefficients will be standardized, and other indices will be transformed into $r$. If effect sizes cannot be extracted, we contact the corresponding author for clarification. Screening, eligibility, and coding agreement will be reported.

Exploration of well-being differences with participant-level meta-analyses. We conduct multilevel mega/meta-analyses on the participant/study level (participants/effects nested in projects nested in nations), and apply meta-analytic structural equation models (Cheung, 2014) to examine (1) the amount of individual differences in well-being, (2) the prediction of these differences by personality, sociodemographic, relationship, and environmental variables, (3) the degree of heterogeneity for all examined personality effects, and (4) explore environmental, sociodemographic, relationship moderators of heterogeneous effects (e.g., whether a personality effect varies across age groups, relationship status, or the degree of COVID-19-related restrictions). In addition, we will explore whether any of the revealed effects vary (5) depending
on the aspect of well-being that is considered, and (6) with the prototypicality of the personality assessment. In a final step, we will (7) repeat all analyses with the pre-COVID-19 data.

Prediction of well-being differences with machine-learning analyses. We create sub-datasets with a maximum number of participants per outcome, single-sided exclude highly-correlated predictor variables \((r \geq 0.8)\) as part of the nested resampling procedure, standardize dependent variables to allow for better comparability, and use regularized linear regression and random forest models to handle correlated predictors. To ensure unbiased estimates, we strictly separate training and test data (Bischl et al., 2012). To build prediction models and identify the most powerful predictors of well-being during COVID-19, we (1) create machine-learning models (linear and nonlinear effects) with a cross-validated, out-of-sample approach to explore how much personality, sociodemographic, relationship, and environmental variables predict well-being, (2) use individual and grouped importance measures ( permutation importance) to identify the most impactful predictors and predictor combinations, and (3) repeat these steps on existing data collected before the pandemic to compare the predictive performance and types of predictors.

WP2: Understanding and targeting individual differences in coping with Corona
In WP2, we aim to understand well-being differences during the COVID-19 pandemic and why they are related to personality and personality-environment interactions. We analyze existing and newly assessed longitudinal data to examine the role of social situation selection (SP1, Munich), interpersonal perception (SP2, Münster), and emotional co-regulation (SP3, Osnabrück). Analyses will reveal (a) how social interaction processes link to well-being, (b) how they differ across individuals and are predicted by personality, and (c) how their effects on well-being are moderated by personality. We apply a theory-driven top-down approach in which we test pre-registered process hypotheses as well as a data-driven bottom-up approach in which we build up machine-learning process models. Additionally, we give personalized feedback to target relevant processes and experimentally test their relevance (see Statistical analyses below).

Own existing datasets
All work groups have already gathered and/or are currently gathering data during the COVID-19 pandemic (see Available own datasets under WP1) that also contain social interaction information and can be used for initial process analyses. Social selection can be analyzed with EMOTIONS-CORONA, SABLE, and PhoneStudy, interpersonal perception processes can be investigated with EMOTIONS-CORONA and CSC, and emotional co-regulation can be analyzed with CSC. As for WP1, there also exist datasets assessed prior to the pandemic that allow for a direct process-wise comparison (the pre-COVID-19 CSC, EMOTIONS, SABLE, and PhoneStudy waves).

New coordinated international data collection
The new data collection allows us to (a) analyze all three classes of processes simultaneously, (b) perform process analyzes across countries and COVID-19 phases, and (c) provide robust process insights in large samples. We collect data with an internationally applied ESM module capturing people’s experiences in everyday live. At selected locations we capture objective situational and behavioral information (social sensing module). Subsamples will participate in a follow-up with personalized process-relevant feedback (targeting module).

ESM module. To sample participants’ experiences in their everyday lives, we apply an open-source web-based application (formR, Arslan et al., 2018) that allows to present customized surveys with a flexible schedule. The ESM module consists of:

- a pre and post trait survey: validated measures of personality (Big Five facets; Honesty/Humility; trait loneliness; values; social/societal attitudes), COVID-19 related habits, attitudes; slower-changing aspects of well-being (e.g., life satisfaction; trait authenticity)
• an **ESM survey** (up to 4 weeks, 4 brief surveys/day) asking for context information and experienced states; for social interaction activities, this includes assessments of
  ○ situation context: interaction yes/no; if yes: info on interaction partner (partner, child, friend, colleague, supervisor, other), interaction context (leisure activity, private task, work), communication channel (face-to-face, phone, videocall, chat)
  ○ well-being: positive affect (happiness), negative affect (worrying, nervousness), state loneliness, state felt authenticity
  ○ interpersonal perception: self-, partner-, metaperceptions; perceived shared reality
  ○ emotional co-regulation: perceived emotional understanding and empathic concern, instrumental and emotional aid, intimacy and warmth, co-brooding, co-reappraisal

The ESM module will be open to all participants with mobile device with access to the internet. We aim at a worldwide sampling strategy, focusing on countries that (a) allow for a broad coverage of different COVID-19-related circumstances, and for which (b) sampling and translation will be supported by confirmed international collaborators (see 6.5). Besides the US and Germany, this will include the Netherlands, UK, Denmark, Sweden, Poland, Estonia, Italy, Spain, Israel, Brazil, and Australia. Within each of these countries, we aim for an age-, gender-, and education-representative sampling. To allow for robust estimates, we will collect at least 500 participants in each country (for the most complex analyses, the cross-level interaction between personality and social process variables on well-being, this gives us a power of >.98 for the detection of small effect sizes in each country; calculations based on a power analysis of simulated data; http://go.wwu.de/xo187). A website describing the CoCo project (incl. FAQs for participants) will be created. Working together with our international collaboration partners, the link to the ESM survey will be distributed widely and the study will be featured via national and local press-releases and media interviews. The study will be communicated as revealing “your personal coping with Corona” and end-of-study personal feedback will be offered (for recommendations: Harari et al., 2017; see Lathia et al., 2017, for a successful application).

**Mobile sensing module.** At selected locations, we additionally collect sensing data continuously during the 4-week ESM phase. This includes objective data on communication (e.g., calls, messages, notifications, app-usage), and behavioral indicators such as music listening, mobility, physical activity, overall phone usage, and day-/night-time activity. To examine the length, repetition, positivity/negativity, and content of communication, we use a keylogging approach and compare each typed word with a lexicon of words clustered in psychologically relevant categories (Linguistic Inquiry and Word Count; see Bemmann & Buschek, 2020). Contextual data focus on the detection of in-vivo conversations but also include geolocations, WiFi and Bluetooth connections, data from online databases (e.g., weather, elevation, air-pollution), and other indicators (e.g., charging status, illumination, environmental noise, headphone status). We make use of established mobile sensing apps and sampling strategies that have been validated and successfully applied in previous projects. In Germany, we investigate university students as well as the general population at three locations (Munich, Münster, Osnabrück) using the PhoneStudy app (Stachl et al., 2020), which is optimized for Android phones (with 73.3% by far the largest share of smartphone users in Germany, Kantar, 2020). To allow for the robust estimation of more complex interactive effects including objectively sensed social context data, we aim at a total sample size of $n = 2,000$. In the US, we examine a student sample within a large ($n = 1,000$) online class at the U Texas (same sampling as in previous SABLE studies) using the app from the professional provider KsanaHealth (additionally including iOS users, the 2nd largest share of smartphone users in the US, Kantar, 2020). Again, we aim at $n = 2,000$ participants (min. of $n = 700$ per semester; fall 2021, spring + fall semesters
Both apps allow us to directly implement the ESM component so that participants will not have to use different tools. In the German student samples, we assess complete longitudinal networks of freshmen. Participants will be able to select their interaction partners (who are participants themselves) via a drop-down menu of photographs taken within an introductory session (see Geukes et al., 2019). This allows us to (a) sample interactions and well-being in a highly dynamic and personally relevant social context, (b) account for the effects of network composition (e.g., some people in social networks influence others’ well-being more than others; Wassermann & Faust, 1994), and (c) to disentangle network selection (e.g., people tend to select friends with similar levels of well-being) and influence (e.g., friends’ well-being predicts changes in target person’s well-being; e.g., van Zalk, et al., 2010).

**Targeting module.** Subsamples of the ESM module participate in a follow-up ESM phase of four weeks and randomly assigned to one of eight conditions, representing six experimental groups that receive personalized feedback (1-3: look-alike feedback, 4-6: individualized feedback), and two control groups (7: generic feedback; 8: no feedback). Following pre-analyzed data from the preceding ESM phase, individuals receive feedback concerning behaviors and thoughts that were most strongly associated with well-being for (1-3) people who are psychologically similar to the individual or (4-6) for this particular individual, respectively. That is, for experimental conditions 1-3 feedback is matched to the participants’ profile on those personality, sociodemographic, and relationship aspects that moderated the link between interaction processes and well-being (i.e., tailored to what behaviors and mental states were most effective in optimizing well-being for individuals with a similar personal profile). For experimental conditions 4-6 feedback is tailored to the participants’ individual prediction models. The six experimental groups receive initial and weekly feedback that focuses on one of the three process domains: situation selection (groups 1 and 4), interpersonal perception (groups 2 and 5), and emotional co-regulation (groups 3 and 6). The look-alike approach (groups 1-3) is conceptually similar to recommender systems such as Amazon’s “People who bought X also bought Y” (Smith & Linden, 2017). Such personalization strategies are gaining traction in disciplines outside of computer science, including personalized medicine and psychotherapy (Chapman et al., 2011), or marketing (Matz et al., 2017). The individualized approach (groups 4-6) goes beyond previous psychological research, and applies within-person insights at time 1 to make recommendations for this particular individual at time 2. The feedback text will be simple to understand and implement, and inform participants that the following thoughts and actions were most effective in securing well-being for individuals with a similar personal profile (1-3) or for him/her (4-6). In line with the analyzed interaction processes, the described thoughts and actions refer to social situations and interaction partners one can select (1, 4; e.g., a social schedule that involves calling friends and family at regular times), to different social reactions one can expect from others (2, 5; e.g., emphasizing a focus on the good will and shared understanding of others), and to different ways of jointly coping with emotional stress (3, 6; e.g., emphasizing a joint focus on meaning making). Process-unrelated recommendations of similar style and length will be used for (7) while no feedback will be given for (8). Further specifics will be delineated following pretesting and a modular set of applicable feedback snippets will be prepared until the start of the project. Participants will be offered to participate in a free test-trial on smartphone feedback that might help them to optimize their well-being during the Corona crisis. Using a conservative response rate of 30% across all participants of the first 4-week-assessment, we expect to collect data for at least n = 3,000 participants, allowing for a powerful test between experimental groups.

**Pretesting.** All modules have been successfully applied in previous projects by the applicants and international collaborators (e.g., ESM: Geukes et al., 2019; Kroencke et al., 2020;
social sensing: Harari et al., 2020; Stachl et al., 2020; targeting: Matz et al., 2017). Final designs will be extensively pretested prior to the project start (ESM + sensing: 2020 fall + 2021 spring semester at UT; early 2021 at LMU; ESM + targeting U Münster + U Osnabrück early 2021).

**Statistical analyses**

We (1) test theoretically derived process hypotheses, (2) build up machine-learning process models, and (3) test the real-life effects of experimentally applied process-oriented feedback.

**Top-down hypothesis testing.** Following existing empirical research on individual differences in social interaction processes and conceptual models on the role of environmental unpredictability (see 1.1 above), we test a set of theoretically-derived hypotheses pertaining to (a) effects of social interaction processes on well-being, (b) the amount of individual differences in these processes and their prediction by personality, and (c) personality-dependent effects of these processes on well-being (i.e., personality moderation). All of the following hypotheses will be differentiated, compared to pre-COVID-19 effects, extended to include further interactions with environmental and sociodemographic characteristics, and preregistered prior to data analysis.

- **Social situation selection (SP1)**
  - (a) no of interactions, face-to-face interactions, and larger variety of interaction partners predict well-being
  - (b) pronounced individual differences in social situation selection (e.g., interaction partners, communication channels); amount and variety of interactions predicted by extraversion; avoidance of social interactions predicted by neuroticism
  - (c) extraverts react with stronger well-being to different sorts of social interactions; people high in neuroticism particularly responsive to interactions with close others

- **Interpersonal perception (SP2)**
  - (a) positivity of other-perceptions, meta-perceived acceptance, and perceived shared reality predict well-being
  - (b) pronounced individual differences in interpersonal perceptions; positivity of other perceptions predicted by agreeableness; meta-perceived acceptance predicted by (low) neuroticism; perceived shared reality predicted by openness and agreeableness
  - (c) neuroticism accentuates the effects of negative other- and meta-perceptions on low well-being; low agreeableness and low neuroticism buffers against the negative effects of lack of perceived shared reality on well-being

- **Emotional co-regulation (SP3)**
  - (a) mimicry in emotional co-regulation predicts well-being: co-brooding predicts decreases in well-being; co-reappraisal predicts increases in well-being
  - (b) pronounced individual differences in emotional co-regulation; neuroticism predicts more co-brooding, and less co-reappraisal
  - (c) neuroticism accentuates the negative effects of co-brooding and weakens the positive effects of co-reappraisal

All of these hypotheses will be tested with state-of-the-art statistical models (multilevel structural equations models, see Hamaker et al., 2018; multivariate network models, see Veenstra, et al., 2013) accounting for the differently nested data structures.

**Bottom-up, machine-learning model building.** This approach allows us to incorporate all process predictors used in the top-down section, while also including them jointly, as well as further variables collected via EMA and mobile sensing. This allows to detect novel but robust process-wise effects on well-being during the pandemic. We proceed in a three-step fashion:

1. To achieve an estimate of generalizability, we use the trained models from WP1 and apply those (without modification) on the data collected in WP2.
2. We create new models for the prediction of well-being including additional data from WP2 and benchmark these models against those created only with personality traits (+ objective sensing data). This allows to investigate how well-being could potentially be predicted from a combination of behavioral, situational, personal (personality traits), and social-process data.

3. We will create new models that will first predict social processes and individual personality scores from sensing data and in a second step use the predicted values in personality and social processes to predict well-being, see Probst et al., 2017, for methodological details). This additional approach will enable us to evaluate to which degree, sensed behavioral and situational data will allow for the automated prediction of social processes, personality traits, and consequently well-being in a stepwise fashion.

For steps 1-3, we will use interpretable machine-learning models to estimate the impact of each of those categories of data on the predictive performance. On a technical level, we will use random forest and elastic net models with appropriate cross-validation (10 x 5 evaluation loop, 10-fold inner, optimization loop). For the sequential modeling in step 3, we will use appropriate resampling techniques for fold creation (e.g., model stacking). During model training, in the inner loop, we will optimize model hyperparameters (Random Forest: mtry, minimum observations per end node; Elastic Net: alpha, lambda, s), perform data pre-processing, case selection, imputation (median for elastic net, 2 times max imputation for random forest models), and data transformations (e.g., centering and scaling for regularization). To promote standardization of machine-learning modeling in the sciences, we will report both absolute and relative performance metrics and detailed information on pre-processing and modeling procedures.

**Personalized feedback analyses.** To realize the targeting module as described before, we create two sets of predictive models for personalized (look-alike and individualized) feedback. First, we use data on personality traits, sociodemographics, and relationship status to detect patterns in sensed behaviors, environmental conditions, and social processes that go along with higher or lower scores in well-being. Further, we create a recommender engine (case-based; Aggarwal, 2016) to predict patterns in behavior and social processes that maximize levels of well-being indicators for different personality trait levels, sociodemographics, and relationship status. Consequently, the output of the model will be used to deliver look-alike feedback to the participants (1-3). Second, we use an idiosyncratic approach and build individual models based on the data obtained from single participants. These individualized models will be trained to detect patterns in behavioral and situational characteristics as well as social processes that correspond to different levels of well-being on a single-person level, specifically. The knowledge-based recommendation (output) of these person-specific models will be used as feedback in the targeting module (4-6). For both model types, we use appropriate cross-validation for unbiased performance evaluation and model optimization. The relevance of different process domains for individual differences in coping with Corona will be tested by (a) comparing the degree of well-being increases from the first to the second ESM phase across experimental groups and (b) testing whether such differences are mediated by an increasingly personalized use of the specifically targeted processes.

### 3 Bibliography concerning the state of the art, the research objectives, and the work programme


Middle East respiratory syndrome coronavirus (MERS-CoV), that may account for one-third of cases. However, the vast majority of cases are community-acquired and reported in travelers returning from the COVID-19 epidemic in the Middle East. The current pandemic has been the result of a novel strain of SARS-CoV-2, which has spread rapidly across the globe. The virus has been found to be highly contagious, with a reported fatality rate of 2% in some areas. The virus is believed to be transmitted through close contact and droplets produced by coughing, sneezing, or talking. The virus is also believed to be transmitted through aerosolized particles, which can linger in the air for a significant amount of time. This has led to the implementation of strict public health measures, including social distancing, mask-wearing, and frequent hand-washing. The impact of the COVID-19 pandemic has been significant, with millions of cases reported worldwide and a number of deaths. The pandemic has also had a significant economic impact, leading to widespread closures of businesses and schools. The situation continues to evolve, with ongoing research and development into vaccines and treatments. However, until a viable solution is found, the public continues to be urged to take precautions to reduce the spread of the virus, including the use of masks, social distancing, and frequent hand-washing.
5 Supplementary information on the research context

5.1 Ethical and/or legal aspects of the project

5.1.1 General ethical aspects

The implementation of studies with human participants is based on the ethical guidelines of the DGP and the BDP (cf. C.III.: Grundsätze der Forschung am Menschen). It also complies with the ethical guidelines of the American Psychological Association (APA) and the June 1964 Declaration of Helsinki (titled “Ethical Principles for Medical research Involving Human Subjects”). All participants will participate on a voluntary basis in exchange for student participation credit and/or aggregated feedback. Risks or harmful consequences for participants are not to be expected. Prior to the studies, participants will be informed about duration and compensation/feedback. Participation will be strictly voluntary. Participants will be informed that they can revoke their participation at any time and without specifying reasons. They will give their informed consent for the scientific use of the data. A large number of similar studies including all kinds of survey, ESM, and sensing data that will be assessed in the CoCo project have already been successfully executed by members of the project team. Ethical approval has been obtained for all three main modules as applied in previous and ongoing projects. Ethical approval for the adapted and integrated design for the new data collection will be obtained once all pre-tests have been analyzed and the local specifics of the COVID-19 pandemic at the time of the start of data collection can be accurately considered.

5.1.2 Descriptions of proposed investigations involving experiments on humans or human materials

Participation in our studies will involve agreement to passive mobile sensing, the repeated completion of brief surveys via people’s smartphones, and the reception of brief written feedback on their self-reported data, none of which is expected to involve a potential risk for participants. Before the start of participation, all participants will be informed about all aspects of the studies and the kinds of data that will be assessed and that they can revoke their participation at any time and without specifying reasons. All aspects of our studies comply with established best practices and ethical guidelines regarding research with human subjects and data handling (also see 5.1.1 and 5.2).

5.2 Data handling

All personal data (i.e., e-mail addresses and pseudonyms used to collect longitudinal data) will be exclusively stored on secure local servers of the three participating German universities (i.e., Osnabrück University, WWU Münster, LMU). These data will be exclusively accessible to employees of the local research teams. Participants can request to delete their data by providing their pseudonym until the last wave of data-collection. After the end of data-collection, data will be merged using pseudonyms and all personal data (i.e., both pseudonyms and email addresses) will be permanently deleted. Participants will be informed that after the end of data collection, the fully anonymized data will be published online (e.g., Datenarchiv PsychDataZPID; Open Science Framework, OSF https://osf.io/). In accordance with best practices in data handling (Harari et al., 2016; Schönbrodt et al., 2017), as well as legal terms (EU General Data Protection Regulations), and in close collaboration with the public open science institute ZPID (https://www.leibniz-psychology.org/), we will very carefully ensure for all classes of data (incl. the sensing data) that all published data is truly anonymized and no data can be used to re-engineer personal information (e.g., by publishing only the extracted behavioral features but not the raw sensing data). Because these anonymized data do not contain pseudonyms, we cannot delete their personal data once we have published these data. For an optimal dissemination of findings and
to allow the research community to replicate our designs and to reproduce our findings and/or reanalyze the data, we will make all materials, data, and statistical code openly available using the tools provided by the OSF and ZPID and applying the FAIR principles (findable, accessible, interoperable, re-useable; see Wilkinson et al., 2016). All applicants are experienced in the application of best open science practices in complex research projects. A preliminary project page has already been created on the OSF: https://osf.io/2tp9/.

6 People/collaborations/funding

6.1 Employment status information
Markus Bühner (100% W3-Professor, tenured), Prof. Dr. Mitja Back (100% W3-Professor, tenured), Prof. Dr. Maarten van Zaal (100% W3-Professur, tenured)

6.2 First-time proposal data

6.3 Composition of the project group
In addition to the PIs listed under 6.1, project team members not funded include

• SP1 (LMU Munich):
  ○ Heinrich Hussman (100% W3-Professor)
  ○ Bernd Bischl (100% W3-Professor)
  ○ Florian Bemmann (100%, E13, TV-L)
  ○ Ramona Schödel (100%, E13, TV-L)
  ○ Larissa Sust (100%, E13, TV-L)
  ○ Timo Koch (100%, E13, TV-L)

• SP2 (University of Münster):
  ○ Katharina Geukes (100% A14)
  ○ Lara Kröncke (50% E13 TV-L)

• SP3 (University of Osnabrück):
  ○ Maor Shani (100% E13 TV-L)
  ○ Stefanie Richters (50% E13 TV-L)

6.4 Researchers in Germany with whom you have agreed to cooperate on this project

6.5 Researchers abroad with whom you have agreed to cooperate on this project
The international cooperation partners of the CoCo project provide important complementary knowledge and experience. Professor Harari, Prof. Matz, and Prof. Gosling have committed to a close collaboration on this project as Mercator fellows (also see 7.5 below) and will be involved in all key steps of the CoCo project. All three Mercator fellows will host one of the PhD students working in the CoCo project during their research stay in the US and will come to Germany for an extended research stay (also see timeline at 7.1.1) during which they will work closely with the other project team members and co-organize one project workshop each (also see 7.6).

Prof. Harari is an Assistant Professor in the Department of Communication at Stanford University. Her research examines how personality is expressed in physical and digital contexts in everyday life. Her main line of research focuses on what digital media, and smartphones in particular, reveal about people’s everyday behavioral patterns (e.g., social behavior, mobility behavior) and psychological characteristics (e.g., dispositional traits, well-being). She takes an ecological approach to conducting her research, emphasizing the importance of studying people in the context of their everyday environments by conducting intensive longitudinal field studies that
combine methods from the social and computer sciences (e.g., surveys, experience sampling, mobile sensing). Since April 2020, she has been collaborating with Prof. Gosling and Dr. Stachl on a smartphone sensing study about the effects of the COVID-19 pandemic on people’s lifestyle behaviors and well-being.

Prof. Matz is the Daniel W. Zalaznick Associate Professor of Business at Columbia Business School in New York. Dr. Matz combines methodologies from psychology and computer science – including machine-learning, experimental designs, online surveys, and field studies – to explore the relationships between people’s psychological characteristics (e.g., their personality, or mental health) and the digital footprints they leave with every step they take in the digital environment (e.g., their Facebook Likes or their credit card transactions). Her work has focused on psychologically-tailored interventions that can use predictions of psychological traits from digital footprints to improve the effectiveness of all-size-fits-all interventions. Recently, Prof. Matz has studied the impact of COVID-19 on mental health, and explored the relationships between personality traits and the pandemic spread and social distancing behaviors.

Prof. Gosling is Full Professor in the Department of Psychology at the University of Texas at Austin. His research focuses on developing and evaluating new methods for assessing psychological traits and the behaviors associated with them. Much of his work focuses on the physical contexts (ranging in scale from living spaces, work spaces, and cafes to neighborhoods, cities, and states) in which ordinary everyday behaviors are expressed and how those spaces reflect and constrain these behaviors. Prof. Gosling is working on a number of projects attempting to understand how contexts and personality may have an impact on behaviors associated with COVID-19 and the measures implemented to contain its spread (e.g., social distancing); this work draws on a range of methods including self-reports in large-scale representative samples, automated smartphone sensing, and analysis of existing large-scale datasets.

We have also agreed to cooperate with a number of further international experts who will provide us with expertise, infrastructure and support regarding the large-scale international ESM data collection. This includes (in alphabetical order): Prof. Erik Amna (Örebro University, Sweden), Prof. Veronica Benet-Martinez (University of Barcelona, Spain), Prof. Susan Branje (Utrecht University, Netherlands), Prof. Jaap Denissen (Utrecht University, Netherlands), Prof. Malgosia Fajkowska (Polish Academy of Sciences, Poland), Prof. Jochen Gebauer (Mannheim University, Germany; University of Copenhagen, Denmark), Prof. Miles Hewstone (University of Oxford, UK), Dr. René Mottus (University of Edinburgh, UK), Prof. Martin Obschonka (Queensland University of Technology, Australia), Prof. Marco Perugini (University of Milan, Italy), Prof. Ricardo Primi (University São Francisco, Brazil), Prof. Anu Realo (University of Warwick UK; Estonian Academy of Sciences, Estonia), Prof. Jason Rentfrow (University of Cambridge, UK), Dr. Maor Shani (Hebrew University of Jerusalem, Israel), Prof. Luke Smillie (University of Melbourne, Australia), Prof. Ingo Zettler (University of Copenhagen, Denmark).

6.6 Researchers with whom you have collaborated scientifically within the past three years
Wiebke Bleidorn, Erika Carlson, Oliver Christ, Filip De Fruyt, Jaap Denissen, Michael Dufner, Gerald Echterhoff, Boris Egloff, Jochen Gebauer, Mario Gollwitzer, Judith Hall, Jens Hellmann, Miles Hewstone, Sven Hilbert, Lauren Human, Stephan Kröner, Marius Leckelt, Daniel Leising, Filip Lievens, Carolyn Morf, Steffen Nestler, Marco Perugini, David Richter, Bernd Schlipphak, Stefan Schmukle, Felix Schönbrodt, Michela Schröder-Abé, Isabel Thielmann, Simine Vazire, Eunike Wetzel, Bart Wille, Cornelia Wrzus, Ralf Wölfer, Matthias Ziegler
6.9 Scientific equipment
The CoCo research team will have access to
- High performance computing (HPC) facilities at the LRZ Garching (LMU Munich)
- an ESM infrastructure (formR) co-hosted at the University of Münster, including accompanying staff for quality control and software development
- supplementary Experience sampling devices (e.g., Nokia 7.2; \( n = 150 \)) at Van Zalk’s Department at Osnabrück University
- The labs of all three PIs as well as those of the international collaborators are equipped with all necessary state of the art technology and infrastructure.

7 Requested modules/funds
An overview over all requested funds split by PI/location can be found in Table 2 below.

7.1 Basic Module

7.1.1 Funding for Staff
A fine-grained summary of all responsibilities and tasks for all funded staff including a detailed timeline can be found in Table 1 below.

LMU (PI Bühner, Markus)
- PhD position (E13 100%): Computer Science/Media Informatics; LMU and coordinated data analyses, mega-analysis machine-learning algorithms; coordination of data collection (preparation) across locations, implementation and maintenance of the mobile sensing module, personalized targeting algorithms; 36 months: €205,200
- PhD position (E13 75%): Psychology; LMU data analyses, mega-analysis pipeline and machine-learning analyses; development of sensing module, study management in Munich, social situation selection analyses, machine-learning analyses, project documentation; 36 months: €153,900
- 1 research assistant (M.Sc. student): Software development, integration of ESM and mobile sensing module, pre-testing of the integrated modules, technical study support, project documentation; 36 months, 10 hours per week: €20,976
- 1 research assistant (M.Sc. student): Data preprocessing, variable extraction for machine-learning mega-analyses, study support, project documentation; 36 months, 10 hours per week: €20,976
- 2 research assistants (B.Sc. student): Data preprocessing, mega-analysis study selection and coding, pretesting of sensing module, recruitment and study support, project documentation; 36 months, 10 hours per week: (2 x €18,001) €36,003

University of Münster (PI Back, Mitja)
- Post-doc position (E14 100%). This position will be taken by Dr. Clemens Stachl (now affil. Stanford University, from October onwards UT Austin). He has several years of academic and industry experience with mobile, sensor-based data collections for personality science and the prediction of outcomes with predictive modeling techniques. His main research
interests focus on the description, prediction, and explanation of objective quantifications of psychologically relevant phenomena in the field - in particular behavior. In his work, he uses consumer electronics for the collection of ecologically valid data (e.g., smartphone sensing, cars) and computational statistics (i.e., machine learning) for data analysis. Clemens will be responsible to coordinate the sensing efforts across all project parts and will instruct PhD students for the individual work packages. At the starting time of the project, Clemens will have experience with working procedures at three of the five institutions involved in the CoCo project (LMU, Stanford University, UT Austin) and will therefore be in a unique position to coordinate the joint efforts. Finally, Clemens has extensive experience in planning, running, and publishing on sensing studies and has already supervised groups of PhD students in similar projects. During the CoCo project, Clemens will flexibly visit the involved institutions to ensure a smooth execution of the project; 36 months: €222,300

- PhD position (E13 75%): Psychology; WWU data analyses, mega-analysis study selection; development of interpersonal perception module, study management in Münster, interpersonal perception analyses, project documentation; 36 months; €153,900
- 1 research assistant (M.Sc. student): Development and pretesting of ESM module, technical study support, project documentation; 36 months, 10 hours per week: €20,619
- 2 research assistants (B.Sc. students): Data preprocessing, mega-analysis study selection and coding, pretesting of ESM module, recruitment and study support, preparation of feedback, project documentation; 36 months; 10 hours per week: (2 x €20,109) €40,218

Osnabrück University (PI van Zalk, Maarten)
- PhD position (E13 75%): Psychology; Uni OS data analyses, mega-analysis coding; development of targeting module, study management in Osnabrück, emotional co-regulation analyses, project documentation; 36 months: €153,900
- 1 research assistant (M.Sc. student): Development and pre-testing of targeting module, technical study support, project documentation; 36 months, 10 hours per week: €24,269
- 2 research assistants (B.Sc. students): Data preprocessing, mega-analysis study selection and coding, recruitment and study support, project documentation; 36 months, 10 hours per week: (2 x €20,859) €41,718
### Table 1 – Project timeline and division of tasks among funded staff

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coordination - data preparation &amp; analyses own data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Preparation &amp; analyses own data WWU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Preparation &amp; analyses own data UU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Preparation &amp; analyses own data Univ OS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination mega-analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Study selection (+ obtaining participant-level data)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Study analyses pipeline</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Study coding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Person-level analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Machine learning analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 1: Mega-analyses well-being trends across countries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 2: Mega-analyses sociodemographic &amp; personality predictors of well-being</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 3: Machine learning approach to identify well-being predictors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 4: The CoCo dataset</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>OSF/ZIPPI documentation 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>WP 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination technical set-up &amp; website creation new data collection</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Technical setup ESM module</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Technical setup sensing module</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Technical setup targeting module</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination process analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Situation selection process analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Interpersonal perception process analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Emotional co-regulation process analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 5: Situation selection differences and COVID-19 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 6: Interpersonal perception differences and COVID-19 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 7: Emotional co-regulation differences and COVID-19 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination final pretesting new data collection</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Final pretesting ESM module</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Final pretesting sensing module</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Final pretesting targeting module</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination international data collection (with ICs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Additional EMA = sensing study Munich, Bonn, Göttingen</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Additional EMA = sensing study UT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Additional EMA = sensing study students (UT)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination new data collection - Targeting</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Situation selection data preparation &amp; analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Interpersonal perception data preparation &amp; analysis</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Emotional co-regulation data preparation &amp; analysis</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 8: Situation selection differences and COVID-19 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 9: Interpersonal perception differences and COVID-19 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 10: Emotional co-regulation differences and COVID-19 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Personalized &amp; individualized feedback analyses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 11: Targeting individual differences during COVID-19</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Paper 12: The CoCo dataset</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordination of press release &amp; press conference</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>OSF/ZIPPI documentation 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>WP 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Digital kick-off meeting (PIs, ICs, Staff, NPs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Digital coordination meeting (PIs, ICs, Staff, NPs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Digital evaluation meeting (PIs, ICs, Staff, NPs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2-day project workshop WWU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3-day project workshop WWU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2-day project workshop Univ OS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research stay (Prof. Metsch to Univ OS, WWU &amp; LUU)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research stay (Prof. Goding to Univ OS, WWU &amp; LUU)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research stay (Prof. Hartig to Univ OS, WWU &amp; LUU)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research stay (PDN WWU at University of Texas, Austin)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research stay (PDN Univ OS at Columbia Business School)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research stay (PDN LUU at Stanford University)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>Staff</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PreDoc WWU &amp; tech PhD WWU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Phd WWU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PhD LUU</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PhD Univ OS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Meeting/Workshop</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Research Stay</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ZPID</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

21
7.1.2 Direct Project Costs

7.1.2.1 Equipment up to € 10,000, Software and Consumables

7.1.2.2 Travel Expenses

LMU (PI Bühner, Markus)
- €2,000/year for national and international conferences for each PhD: 2 PhDs * 3 years * €2,000 = €12,000
- PhD: Visit Stanford (Prof. Harari) for 6 months; €7,500 (flight + accommodation)
- Travel costs of €284 (train rides to Münster and Osnabrück and back) for 2 project team meetings for each PhD and PI: 3 (2PhDs+PI) * €284 = €852

University Münster (PI Back, Mitja)
- €2,000/year for national and international conferences for each PhD/PostDoc: 2(PhD+PostDoc) * 3 years * €2,000 = €12,000
- PhD: Visit Austin (Prof. Gosling) for 6 months; €7,500 (flight + accommodation)
- Travel costs of €157 (train rides to Munich and Osnabrück and back) for 2 project team meetings for PhD, PostDoc, and PI: 3 (PhDs+PostDoc+PI) * €157 = €471

Osnabrück University (PI van Zalk, Maarten)
- €2,000/year for national and international conferences for PhD: 1 PhD * 3 years * €2,000 = €6,000
- PhD: Visit New York (Prof. Matz) for 6 months; €7,500 (flight + accommodation)
- Travel costs of €157 (train rides to Munich and Münster and back) for 2 project team meetings for PhD and PI: 2 (PhDs+PI) * €157 = €314

7.1.2.5 Other Costs

For the most extensive ESM plus mobile sensing studies involving the general population (in addition to student networks for which research participation credit will be provided) participants will receive additional monetary compensation for their participation (40€ for 4 week participation).

- Incentives for Studies located in Munich (PI Bühner)
  - Experience Sampling incl. Sensing 4 weeks: €40 x 600 participants x 3 waves (fall 2021, spring and fall 2022) = €72,000
  - Printing flyers and advertising: €500

- Incentives for Studies located in Münster (PI Back)
  - Experience Sampling incl. Sensing 4 weeks (€40 x 600 participants x 3 waves (fall 2021, spring and fall 2022) = €72,000
  - Printing flyers and advertising: €500

- Incentives for Studies located in Osnabrück (PI van Zalk)
  - Experience Sampling incl. Sensing 4 weeks (€40 x 600 participants x 3 waves (fall 2021, spring and fall 2022) = €72,000
  - Printing flyers and advertising: €500
For the ESM plus sensing studies at UT in Austin the app of the professional provider KsanaHealth will be used, allowing to reach Android and iOS users (with the latter being a major group of smartphone users in the US). The costs for app provision, pretesting, quality control and service amounts to 25,000 € per study. The three waves of data acquisition (fall 2021, spring + fall 2022) will, thus, amount to 3 * 25,000€ = **75,000€**, administered at Münster (PI Back).

5,000€ (administered at Münster, PI Back) are requested for the professional translation of ESM surveys and targeting feedback to allow for the international application of the ESM and targeting modules.

### 7.1.2.6 Project-related Publication Expenses

We request publication costs for open access publications of 750€/year for each PI / location, that is, 3 * 750 = **2,250€** for each PI/location.

All submissions will be written in English to ensure the broad international reception of project results. Therefore, **1,500€** is requested for each PI / location for the linguistic review of all manuscripts by a native English speaker.

### 7.5 Module Mercator Fellows

All three international collaboration partners (Prof. Gosling, Prof. Harari, Prof. Matz; see 6.5) have agreed to be part of the CoCo project team and to take part in an intensive and long-term exchange as Mercator fellows during the 3-year period of the project (also see collaboration agreements). For each of the three fellows, this will include the hosting of one of the projects PhD students in the US, a 3-months stay in Germany, and a continuous exchange and involvement in all steps of the project before and after this research stay. We are only applying for travel costs of €4,500 (flight + accommodation) for each Mercator fellow (= 13,500 € in total). Each fellow will be hosted by one of the three PIs, so each PI applies for **4,500 €**.

### 7.6 Module Workshop Funding

We will hold three 2-day project workshops, one during each of the stays of the Mercator fellows, that is, one at each of the three locations (LMU Munich, U Münster, U Osnabrück). These workshops are thought to present project findings to and engage in a deepened discussion with the wider scientific community as well as to introduce early career researchers to the topic and project. Each workshop will be devoted to one hot topic related to the CoCo project (1: Capturing CoCo: How can we assess differences in coping with Corona, 2: Understanding CoCo: Why do we differ in coping with Corona?, 3: Targeting CoCo: How can we transfer scientific insights to enhance coping with Corona?) and consist of (a) a keynote by the Mercator fellow, (b) talks by invited guests from neighboring disciplines (e.g., sociology, philosophy, economics, political science, medicine, computer science) of the respective university, (c) a methodologically-oriented workshop, (d) a poster session covering results of the CoCo project, and (e) a panel discussion. Each workshop will be open to staff from the respective universities, all CoCo project members and up to 10 German early career researchers interested in the topic who can apply for participation and for whom travel costs (train and accommodation) will be covered. Selection will be based on performance criteria (considering the early career stage), thematic fit, a good coverage of different disciplines, equal representation of gender and further diversity criteria. To
cover the travel costs of selected early career researchers, we apply for \(10 \times 500 = 5,000\€\) for each workshop (that is for each PI/location). A virtual workshop following the same basic structure will be held in case of COVID-19 related restrictions in which case money to cover travel costs will not be needed. All further facilities, infrastructures, and personnel support for holding these workshops (both face-to-face and virtual) are in place at all three PI locations.

7.7 Module Public Relations Funding

The PIs have established close collaborations with the local public relations and science communications offices at their universities and will work closely together with them to organize press releases and press conferences following the finalization of both WPs. Also, a project website will be launched by which we provide accessible summaries of the project’s results for the general public, link to the repository, and announce project updates and events. In addition, to allow for a broader, more effective, sustainable, and high-quality science communication, we will provide a 2 months stipend for a “journalist in residence (JiR)” who will get to know the research team and get detailed insights into the conceptual and methodological background, the research activities, and the results of our project. The JiR will write a number of high quality science communication pieces that allow for a prominent national and international coverage. S/he will coordinate his/her activities closely with the local public relations and science communications offices. To cover this stipend we apply for €3,500 /month (e.g., see https://www.wzb.eu/de/presse/journalist-in-residence-fellowship), that is, €7,000 in total (PI Back/Münster).

Table 2 – Overview of requested funds split by PI/location

<table>
<thead>
<tr>
<th>Module</th>
<th>PI Bühner (Munich)</th>
<th>PI Back (Münster)</th>
<th>PI van Zalk (Osnabrück)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.1.1</td>
<td>€ 437,055</td>
<td>€ 437,037</td>
<td>€ 219,887</td>
</tr>
<tr>
<td>7.1.2.2</td>
<td>€ 20,352</td>
<td>€ 19,971</td>
<td>€ 13,814</td>
</tr>
<tr>
<td>7.1.2.5</td>
<td>€ 72,500</td>
<td>€ 152,500</td>
<td>€ 72,500</td>
</tr>
<tr>
<td>7.1.2.6</td>
<td>€ 3,750</td>
<td>€ 3,750</td>
<td>€ 3,750</td>
</tr>
<tr>
<td>7.5</td>
<td>€ 4,500</td>
<td>€ 4,500</td>
<td>€ 4,500</td>
</tr>
<tr>
<td>7.6</td>
<td>€ 5,000</td>
<td>€ 5,000</td>
<td>€ 5,000</td>
</tr>
<tr>
<td>7.7</td>
<td>-</td>
<td>€ 7,000</td>
<td>-</td>
</tr>
<tr>
<td>Total sum</td>
<td>€ 543,157</td>
<td>€ 629,758</td>
<td>€ 319,451</td>
</tr>
</tbody>
</table>