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COVID protection behaviours, mental health, risk perceptions and control beliefs: A dynamic temporal network analysis of daily diary data

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Abstract

Background: To control infections, behavioural non-pharmaceutical interventions (NPIs) such as social distancing and hygiene measures (masking, hand hygiene) were implemented widely during the COVID-19 pandemic. At the same time, adherence to NPIs has also been implied in an increase in mental health problems. However, the designs of many existing studies are often poorly suited to disentangle complex relationships between NPI adherence, mental health symptoms, and health-related cognitions (risk perceptions, control beliefs).

Purpose: To separate between- and temporal within-person associations between mental health, health-related cognitions and NPI adherence.

Methods: Six-month ecological momentary assessment study with six 4-day assessment bouts in 397 German adults. Daily measurement of adherence, mental health symptoms and cognitions during bouts. We used dynamic temporal network analysis to estimate between-person, as well as contemporaneous and lagged within-person effects for distancing and hygiene NPIs.

Results: Distinct network clusters of mental health, health cognitions and adherence emerged. Participants with higher control beliefs and higher susceptibility were also more adherent (between-person perspective). Within-person, similar findings emerged, additionally, distancing and loneliness were associated. Lagged findings suggest that better adherence to NPIs was associated with better mental health on subsequent days, whereas higher loneliness was associated with better subsequent hygiene adherence.

Conclusion: Findings suggest no negative impact of NPI adherence on mental health or vice versa, but instead suggest that adherence might improve mental health symptoms. Control beliefs and risk perceptions are important covariates of adherence - both on between-person and within-person level.

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Introduction

At the time of writing (July 2023), the COVID-19 pandemic had been an ongoing public health emergency, with roughly 770 million confirmed cases and more than 6.9 million deaths worldwide [1]. Even though highly effective vaccines protecting against death and severe illness course are widely available (with more than 13 billion doses being administered until July 2023; [1]), a (re-)infection with COVID-19 is associated with an increased risk for long-term ill health consequences such as impaired immune functioning, neurological problems and fatigue (Long COVID; [2]). Besides the substantial physical illness and mortality burden associated with COVID-19, there has been a marked increase in mental health issues as well. In particular depression and anxiety levels were significantly increased in general populations when compared to pre-pandemic levels [3, 4]. One nationally representative, longitudinal study of adults in the United Kingdom showed that contracting COVID-19 early in the pandemic was associated with long-lasting associations with negative mental health up to 13 months later [5] Together, these studies suggest a substantial and potential lasting increase in depression and anxiety symptoms since the pandemic started, and the increase is likely due to both the course of the pandemic and to consequences of measures to reduce COVID infections [6]. In this study, we examine how adhering to these measures could be associated with such increases in mental health problems.

Measures to reduce COVID infections include so-called non-pharmaceutical interventions (NPIs) and were implemented by most countries during the first two years of the pandemic to mitigate the impact and reduce transmission. These NPIs included different individual behavioural measures (e.g., hygiene measures such as mask wearing, hand hygiene or keeping a social distance) and structural measures (e.g., school and university closures, reductions in cultural activities, furlough schemes to avoid mass unemployment). The degree to which NPIs were implemented differs on a continuum from being mandatory to being recommended with appeals to personal responsibility. For example, in Germany, the context of this study, mask-wearing continues to be mandatory on public transport, whereas mask-wearing in public spaces is simply recommended.

While both individual and structural NPIs have been highly effective in reducing the transmission of SARS-CoV2 [7], some of these interventions have been implied to impact on mental health above and beyond the pandemic itself [8]. For example, NPIs such as the recommended reduction of interpersonal contacts, closing of schools, universities and social meeting points have reduced opportunities for social exchange. As a result, it has been hypothesised that available social support has reduced and feelings of loneliness have increased, which in turn may have led to increases in depression [9]. Other NPIs such as mask mandates, for example, have been discussed in conjunction with both negative as well as positive effects on mental outcomes through decreased or increased levels of perceived control over the health threat through COVID-19 [10].

At the same time, mental health could also affect adherence to recommended protective behaviours. For example, a longitudinal study in older American women found that more depressive symptoms during the pandemic were associated with worse cognitive status, which in turn predicted lower adherence to recommended protective behaviours [11]. An Italian study suggests that the co-occurrence of anxiety and depression - and associated rumination and information-seeking online - was associated with lower adherence to public health recommendations, whereas higher trait anxiety was associated with better adherence to recommendations [12].

A positive association between anxiety and adherence could be plausible as well, as health cognitions associated with anxiety such as a perception of an increased personal risk of infection have also been implicated with better adherence to hygiene measures or social distancing. For example, Norman et al. [13] and Schüz et al. [14] found higher perceptions of being at risk of infection with COVID-19, and higher perceptions of the severity of the illness to be associated with an increased likelihood to adhere to a range of recommended protective behaviours. Such associations would also be implied in health behaviour theories such as the Health Belief Model [15] or Protection Motivation Theory [16]. However, at the same time, adherence was also significantly—and with larger effect sizes—predicted by control beliefs such as autonomy and capability cognitions, which are also implied in lower feelings of COVID-related anxiety [13, 14]. While by no means complete, these example studies contribute to an overall heterogeneous picture of the relationship of adhering to COVID protective behaviours, mental health indicators, and risk perception as well as control beliefs. This is potentially problematic, as in order to mitigate the mental health impact of NPIs and adherence, we need to better understand the underlying mechanistic relations between cognitions such as control beliefs as well as risk perceptions, adherence behaviours, and symptoms of poor mental health.

One plausible cause for the heterogeneity in previous findings on the associations between mental health, adherence to NPIs and risk cognitions is that the cross-sectional or baseline-follow-up designs of most studies are not suitable to adequately depict the reciprocal and temporal relationships between these factors, which in turn prevents mechanistic insights [17, 18]. Essentially, this relates to a mismatch between the need to discover what are essentially within-person mechanisms (e.g., it is assumed that if a person perceives an increased risk of being infected, they will increase their efforts to protect themselves from infection) in studies that are at best able to illustrate between-person differences (e.g., persons who perceive a higher risk of being infected also report higher levels of protective behaviours; [19-21]). This issue is exacerbated by the fact that many of the theories implied in the relationship between adherence behaviour, mental health indicators, risk perception and control do not specify temporal dynamics or potential reciprocities between these variables [22, 23]. The need for studies that can detect such mechanistic associations is increasingly being recognised in behavioural research [19, 24], but requires studies with a high frequency of short-term repeated measurements and analytic frameworks that can differentiate between-person differences from within-person associations, both contemporaneously and in terms of temporal dynamics over time [25].

Temporal dynamic network analysis based on multilevel vector autoregressive network models [26] has been suggested to be useful for such questions [27]. Here, reciprocal relationships between variables can be disentangled both in terms of separating between-person differences from within-person associations, and in terms of differentiating within-person associations between contemporaneous (i.e., at any given time point) from temporal (i.e., associations over time). For example, the question whether and how variable x (e.g., perceiving anxiety symptoms) is associated with variable y (e.g., adhering to COVID protective behaviours) can be disentangled into the *between-person* question whether persons with a generally higher level of x also show generally higher levels of y. At the same time, we can examine within-person associations such that whether perceiving e.g., *higher levels of x than normally* at any time point is associated with perceiving *higher levels of y than normally* at the same time points (*contemporaneous within-person association*). In addition to this variance separation in between- and within- person differences, temporal dynamic network analysis also allows examining mechanistic processes, in particular whether higher levels of variable x at a time point *t* are associated with higher levels of variable y at the subsequent time point *t + 1*, or whether indeed higher levels of y at *t* are associated with higher levels of x at *t + 1*, and testing these bivariate associations against each other (*lagged within-person association*). Importantly, this also allows examining feedback processes in which changes in x might elicit changes in y, which in turn might elicit changes in x, for example in negative feedback loops implied in behaviour change processes [23]. Only few studies have employed temporal dynamic network analysis in the context of mental health during the COVID-19 pandemic. For example, Ebrahimi et al [28] show that experiences of helplessness during the pandemic increase depressive symptoms and identified particular risk factors for carry-over effects. Haucke et al. [29] compared networks between lockdown and non-lockdown periods in Germany and found increases in loneliness during lockdown periods, which in turn predicted worse mental health.

However, the role of actual adherence to individual NPI behaviours in relation to mental health indicators, and the potentially reciprocal interrelations between these factors and modifiable determinants of adherence behaviour such as control beliefs and risk perceptions is unclear. Disentangling this relationship would both provide better insight into the complex relationship between adherence to NPIs and mental health, and identify possible resources for better mental health within these processes. More importantly, it could help uncover potential mechanisms linking adherence to NPIs to mental health. Therefore, the main aims of this study are to examine both the between-person differences, within-person associations and temporal dynamics implied in adherence to NPIs, mental health indicators, and risk perceptions as well as control beliefs.

Method

Study methods and results are reported following the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement [30] and the Checklist for Reporting Results of Internet E-Surveys (CHERRIES; [31]).

Context and setting

We conducted a six-month ecological momentary assessment (EMA) study with six four-day assessment bouts across Germany between August 17, 2021, and August 13, 2022 (for sampling scheme, see Figure 1). This 12-month period saw substantial changes in the extent of the pandemic (7-day incidence rates per 100,000 inhabitants varying between 72.1 on August 27,2021 and 1,732 (March 21, 2022), with 708 (July 7,2022) towards the end of the study) as well as in the regulations related to NPIs in Germany. During the time, nationwide mandatory mask-wearing mandates in public spaces and transport were re-introduced (November 2021), and vaccination checks including past infection or a negative current test result before entering health services, restaurants or entertainment venues were in place. On April 3, 2022, these mandates expired save for health service locations and public transport. At the beginning of the study, roughly 60% of the eligible German population had been vaccinated twice; this increased to 70% in December 2021 and plateaued on this level. The data collection period of this study thus covered a time with substantial dynamics in the pandemic situation, high COVID-19 incidences and slow progress in the vaccination program paired with a roll-back of mandatory NPIs. No a-priori power analyses were conducted, as the existing literature did not allow extracting usable effect size estimates. However, the realised sample size is sufficient to detect small interaction effects in multilevel models with power > .8 [32].

Ethical approval for the study was obtained from the University of Bremen ethics committee (Ref 2021-11). Measurement instruments, a study description and (de-identified) data can be obtained in the online study repository (https://osf.io/ks6q4/). Research questions and analyses for this study were not preregistered.

Procedure

All instruments and procedures were pilot tested within the participating institutions and, where necessary, revised. Participants were recruited via online advertisements in multiple social media networks (>60,000 exposures) and additional off-line advertisement material (posters, flyers) in large German cities. Participants were directed to the public study website (open survey format), on which they were provided with information about the study aims and duration as well as data storage and protection (password-protected GDPR compliant servers). After providing informed consent (online), they could self-enrol by opening a QR-code to then install the ExpiWell-EMA app (available on Android and iOS; www.expiwell.com). This multi-step procedure also served to minimise the risk of bots enrolling in the study. Participants were then prompted to fill in a baseline questionnaire through the app (average completion time: 20 minutes). To reduce participant burden, some additional baseline questions were spread across the first four daily evening reports (for additional information on the specific questionnaire structure, please see the online study repository (https://osf.io/ks6q4/). The day after joining the study, the EMA phase with four assessment days per month for a total duration of six months started (for a visualisation of the sampling scheme, see Figure 1).

Figure 1 about here

During assessment bouts (see Figure 1), each day, participants were prompted at five semi-random time points across several non-overlapping sampling windows (“random assessments”; not reported here) and completed an end-of-day assessment (“evening report”). Evening reports were available from 8 pm to 11pm each monitoring day, and participants received a reminder after ten minutes with an option to snooze. In total, participants completed 5882 of 20,222 scheduled evening assessments (mean = 10.28, SD = 8.19, min = 0, max = 24, compliance = 29.09%). Participants could choose not to answer questions, and could review their answers before submitting. On average, these assessments were completed in five-and-a-half minutes (SD = 5.32 minutes; IQR: 2.76 - 6.29). Participants had the opportunity to opt-out of the study after three months and receive either 40 Euros in case they had completed a minimum of 80% of all random and evening prompts combined. If participants did not willingly opt-out of the study, they were enrolled for another three months and received a total of 60 Euros in case they reached an equal amount of compliance.

Measures

All measures used in this study can be found in full detail in the online study repository (https://osf.io/ks6q4/). In the current manuscript, we only report selected items relevant to our specific research questions from the baseline questionnaires and evening reports.

The baseline questionnaires consisted of 103 questions in total. Participants reported demographics (e.g., age, gender), their current living conditions, whether they had contracted Covid-19 before, and whether they had been vaccinated against it. Educational attainment was assessed in line with categories of the CASMIN classification [33] which were adopted to the German educational system and thus ranged from elementary education attained (1) to full vocational maturity (7). We assessed participants´ capabilities to find, assess and use health-related information with the European Health Literacy using the Survey Questionnaire (HLS-EU-Q16; [34]). To reduce the loss of information that results from scoring “very difficult” and “difficult” answers both as 0, and “easy” and “very easy” answers as 1, we instead scored these items with a range of 0 to 3 when creating the scale total value.

The daily evening reports during the assessment bouts consisted of 39 questions and took participants on average 5-and-a-half minutes to complete. Here, we used the Patient Reported Outcome Measurement Information System - Short Form (PROMIS; [35]) to indicate depressive symptoms (4 items; example items: “I felt depressed today”, “I felt worthless today"), anxiety symptoms (4 items; example items: "I felt fearful today", "My worries overwhelmed me today"), emotion dysregulation (3 items; example item: "I felt grouchy today"), and loneliness (1 item; "I felt lonely today"). All items were answered on a slider scale anchored at 0 ("never") and 100 ("all the time"). Risk cognitions were assessed based on the recommendations in [36]. *Vulnerability* was assessed referring to the individual themselves ("How concerned are you about your personal health (in the face of the current pandemic) today?") and to relevant others ("How concerned are you about the health of family and friends (in the face of the current pandemic) today?"), both answered on a 0-100 slider scale anchored at 0 ("not at all") and 100 ("very concerned"). *Risk perceptions* were assessed as *susceptibility* ("How likely do you think it is today that you will contract the Corona virus?"), answered on a 0-100 slider ("not at all" - "very likely"), and as *severity* ("How serious do you think an infection with the Corona virus would be for you today?"), answered on a 0-100 slider ("not at all" - "very serious"). Day-level adherence to behavioural recommendations regarding hygiene behaviours (hand hygiene and mask wearing) as well as social distancing ("I followed the current guidelines regarding [hygiene/social distancing] today."; 0-100 slider, anchored "not at all" to "absolutely") was assessed using combined behaviours in each domain [37]. Additionally, participants reported their momentary *perceived behavioural control* ("How hard did you find it to follow the current guidelines regarding [hygiene/social distancing] today?"; 0-100 slider, anchored"not at all" to "very hard"). The *perceived behavioural control* items were then recoded such that higher scores reflect higher perceived control. See Table 1 for descriptive statistics of all variables in the study.

Table 1 about here

Analyses

In order to capture temporal relations between adherence, risk perceptions, perceived behavioural control and mental health indicators, we estimated multilevel vector autoregressive network models using the R package mlVAR [38]. Here, individual parameters are sampled from a shared probability distribution, with a two-step modelling approach allowing us to separate within- from between-participant variation over time. First, node-wise multilevel regression models with within-person centred lagged (lag-1) predictors as well as person-means are estimated. These models estimate a) *lagged within-person associations* and b) *overall between-person association*s. Second, node-wise multilevel regression models are estimated with the step-1 residuals and thus yield c) *contemporaneous within-person associations* (without auto-regressive effects modelled in step 1). We then visualised the resulting networks of nodes (variables) and edges (relations) using the R package qgraph [39]. We ran separate analyses for adherence to hygiene and distance NPIs, as the relationships between these NPIs, mental health and risk as well as control perceptions could vary due to differing demands and implications. Models were estimated with missing data of included cases (see below) using the maximum likelihood estimator in mlVAR.

Results

Of the total 623 participants enrolled in the study, only 397 (63.7%) provided enough repeated measurements with no missing data across all variables [26] to be included in the analyses reported here (total included evening assessments: 5452, mean of 13.7 per person). We included all participants who provided at least the minimum amount of data required for the mlVAR models to be estimated [26]. Of the remaining participants, 298 identified as female (75.06%), 64 identified as male (16.12%), and 3 as “other” (0.76%). On average, participants were 33.95 years old (SD = 13.25, range = 18 - 69), 9.32% reported at least one of their parents to not have German citizenship and most of the participants were well-educated (32.99% reporting at least a Bachelor´s degree). The 226 participants excluded from the following analyses were three years younger on average (M_{excluded} = 30.79, M_{included} = 33.95 and, accordingly, were less likely to have already completed higher education (only 26.55% had reached at least a Bachelor´s degree). However, they did not differ significantly regarding any of the focal outcomes of the analyses at baseline (depressive symptoms: mean difference = 5.99, 95% CI [-1.05, 13.02], $t(87.61) = 1.69$, $p = 0.09$; anxiety symptoms: mean difference = 2.55, 95% CI [-3.82, 8.93], $t(89.86) = 0.80$, $p = 0.43$; dysregulation symptoms: difference = 2.88, 95% CI [-4.02, 9.78], $t(93.35) = 0.83$, $p = 0.41$). A detailed description of the larger sample has been reported elsewhere [40].

Between-person relationships

Figure 2 shows the dynamic network model for between-person relationships (edges) for distancing behaviours and hygiene behaviours. Only significant edges ($p < .05$) are shown.

Figure 2 about here

For distancing behaviours, we observe distinct networks of risk-related cognitions and mental health symptoms, with small relationships between depression and susceptibility as well as anxiety and vulnerability (others). We also observe between-person relationships between risk perceptions and adherence such that persons who report more adherence behaviours also report higher perceived risks (for others) and higher susceptibility, and we observe a substantial positive association between adherence and perceived behavioural control. For hygiene behaviours, we observe similar distinct networks. Positive associations indicate that individuals with higher levels of susceptibility and perceived behavioural control also report higher levels of adherence to hygiene recommendations. Here, we also observe an association of higher depressive symptoms with susceptibility, of anxiety with vulnerability (others), and of loneliness and severity. A negative relationship indicates that individuals with higher perceived behavioural control also perceive lower vulnerability (self).

Contemporaneous relationships (within-person)

Figure 3 shows the dynamic network model for contemporaneous within-person relationships (i.e., associations during any given day). Again, only significant edges ($p < .05$) are shown.

Figure 3 about here

For distancing behaviours, we find three distinct networks. A first network combines risk-related cognitions (vulnerability self/others and severity as well as susceptibility) with substantial intra-network correlations. A second network comprises mental health indicators with substantial correlations between symptoms of depression, anxiety, dysregulation and loneliness, and a third behavioural network links perceived behavioural control and social distancing behaviour. Small but significant negative associations exist between perceived behavioural control and vulnerability (self) as well as susceptibility, and between susceptibility and anxiety. Within any person and during any one day, higher adherence to distancing behaviour is positively associated with loneliness, and anxiety is negatively associated with perceived behavioural control.

Findings for hygiene behaviour largely mirror those for distancing behaviours: We find three distinct networks, with strong interrelations between vulnerability cognitions in the risk perception network as well as anxiety and depression symptoms in the mental health network. Higher levels of anxiety are contemporaneously associated with higher levels of vulnerability and susceptibility. Perceived behavioural control and adherence are positively associated, and higher perceived behavioural control is associated with lower susceptibility (and vice versa). However, here, we find no contemporaneous relationship between adherence and loneliness.

Temporal (lagged) relationships

Finally, temporal (lagged) relationships indicate positive or negative within-person relationships between one variable on any given day and another variable on the subsequent day. Figure 4 shows the dynamic network model, with only significant relationships displayed.

Figure 4 about here

For distancing behaviours, we find strong autocorrelations (indicated by circles) in most cognitions and in dysregulation as well as anxiety. The mental health network shows weaker internally interrelations, but in the health cognitions network, recursive positive feedback loops can be observed between susceptibility, vulnerability (self) and vulnerability (other). Higher control at t-1 is associated with higher adherence the following day. We also observe associations between adherence and subsequent mental health indicators More adherence at t-1 is related to better mental health (lower levels of symptoms) on the following day. Depressive symptoms at t-1 are related to higher vulnerability for others on the next day, higher anxiety at t-1 is associated with higher depression on the following day. Loneliness has no temporal associations with any other variable in the networks.

For hygiene behaviours, we observe that adherence at t-1 is associated with lower depressive symptoms and higher control beliefs on the subsequent day, similar to distancing behaviours. However, loneliness at t-1 predicts better adherence to hygiene the subsequent day. The network of risk cognitions is again characterised by substantial autocorrelations and internal relations, and we observe similar positive feedback loops in the vulnerability and susceptibility cognitions.

Discussion

This study examined the temporal dynamics involved in adherence to mandated and recommended non-pharmaceutical interventions (social distancing and hygiene measures), behavioural control, risk cognitions, and indicators of mental health over 6 months during the COVID-19 pandemic in Germany. Using dynamic temporal network analysis, we were able to disentangle between-person from within-person associations, and could also illustrate the temporal (lagged) relationships between adherence behaviours, risk cognitions and indicators of mental health. This disentanglement is crucial, as findings of associations on one level do not necessarily generalise to others, and differences *between* individuals are not necessarily indicative of changes and associations over time *within* individuals [19-21].

In all analyses, we found distinct and separable networks for indicators of mental health (symptoms of depression, anxiety, dysregulation and loneliness) and cognitions, with substantial interrelations each. *Between-person analyses* show that individuals who perceive higher illness risks and perceive higher control over behaviour also report higher adherence, and that individuals who report more depression and anxiety symptoms also report higher levels of risk perceptions and vulnerability. Within-person *contemporaneous analyses* indicate that higher anxiety on any day was associated with higher vulnerability and susceptibility beliefs. For distancing behaviours, higher perceived behavioural control was related to lower risk perceptions. For hygiene behaviours, higher adherence was related to higher levels of anxiety. In the within-person *lagged (temporal) analyses*, we found that more adherence to social distancing behaviours was associated with *better* mental health on the following day on all indicators, and that more adherence to hygiene measures was associated with fewer depressive symptoms on the following day.

Mental health and adherence behaviour

One of the key aims of this study was to examine relationships between indicators of mental health and adherence to behavioural recommendations to reduce COVID infections. We examined this using between-person and within-person analyses. In *between-person* analyses, we found no interpretable relationships between mental health indicators and adherence behaviours. Changing the perspective to *contemporaneous within-person* associations, we found a (small) contemporaneous relationship between momentary adherence to social distancing behaviours and loneliness - but not depressive symptoms. In hygiene behaviours, we identified a small but significant within-person contemporaneous association between anxiety and adherence. It seems plausible to interpret this association to indicate that adherence to hygiene measures serves as a means for individuals to regulate anxiety given that both vulnerability (self) and susceptibility were associated with anxiety, and knowing that reducing these cognitions can motivate health behaviour change (e.g., [41]).

Looking at *temporal (lagged) within-person* associations, we found that adhering to social distancing on any day was associated with lower depressive symptoms - as well as lower levels of dysregulation, anxiety and loneliness on the subsequent day. Together with the lack of within-person contemporaneous relationships between adherence to distancing and depression, this is particularly noteworthy, as it could suggest that adhering to social distancing recommendations, which inevitably bring a reduction in in-person contact, did not necessarily result in higher levels of distress on the following day (or on the same day), but rather, higher adherence could, e.g., through feelings of accomplishment foster, *lower* levels of distress. However, the reverse association seems plausible as well - that lower levels of adherence on t-1 were associated with higher levels of depression, anxiety, dysregulation and loneliness symptoms on the following day. The key here might be the finding that social distancing was not associated with experiencing loneliness on the next day, thus eliminating one possible link to poor mental health [8, 9]. At the same time, it needs to be borne in mind that the lagged temporal effect is a within-person effect - this means that following days where adherence was higher than the within-person average, this person experienced lower levels of depression, anxiety, loneliness and dysregulation. From a between-person perspective, these levels could still be high.

Temporal (lagged) relationships between adherence to hygiene and mental health look somewhat different: Higher loneliness was associated with higher levels of adherence to hygiene behaviours on the next day - which could indicate that, in order to reduce experiences of loneliness, participants might have chosen to apply protective measures and engage in in-person social contact on the following day. Similar to distancing behaviours, higher levels of hygiene adherence were associated with lower levels of depression on the following day. The positive lagged effect of hygiene adherence on perceived control suggests that adherence could have increased participants' sense of achievement, which in turn could have improved depressive symptoms.

Mental health and risk cognitions

In all (between-person, within-person contemporaneous and within-person lagged) network analyses for both adherence behaviours, we found distinct networks of strongly interrelated mental health indicators and risk cognitions. In *between-person* analyses (controlled for within-person processes), we found associations between these networks in that individuals who have a higher disposition to experience depressive symptoms were also more likely to perceive a higher susceptibility to COVID-19. This is in line with previous research that found associations between risk cognitions related to COVID-19 and depressive symptoms (e.g., [42, 43]), albeit mainly in cross-sectional rather than in within-person analyses. However, we could not identify contemporaneous or lagged within-person relationships between depressive symptoms and risk cognitions. This suggests that these previous findings might reflect between-person differences rather than within-person processes. This is important insofar as it suggests that such associations could be the result of third variables that influence both risk and mental health cognitions, and makes mechanistic associations between these variables less likely.

For both hygiene and distancing behaviours, we identified positive within-person contemporaneous associations between anxiety and momentary risk cognitions (self-related vulnerability and susceptibility), indicating that on days when participants experienced higher-than-usual vulnerability and risk, their anxiety was also higher than usual - and lower levels of risk were associated with lower anxiety. This finding is largely consistent with research indicating that both in the early days of the pandemic (March 2020; [44]) and over the course of the pandemic (e.g., November 2021; [45]), higher perceptions of personal risk were associated with higher levels of anxiety. The association between anxiety and individual risk perceptions has also been reported in the context of earlier epidemic outbreaks such as the outbreak of SARS in Hong Kong 2003 [46]. It is also consistent with theoretical assumptions that assume that at least trait anxiety increases the propensity of individuals to perceive themselves at risk for negative outcomes, and the negative contemporaneous association between anxiety and perceived behavioural control could be interpreted to support this idea as well - perceiving the ability to minimise the risk of infection through adherence to mitigation strategies should also be associated with lower anxiety [47, 48]. At the same time, it is possible and plausible that the relationship between contemporaneous risk perceptions and anxiety is reciprocal - repeatedly increased momentary risk perceptions might increase more stable levels of (trait) anxiety, and at the same time, trait anxiety could affect the calibration of the experience of personal risk such that similar objective risks are perceived to be higher in individuals higher in trait anxiety [49]. Supporting this notion, we also found individuals with a disposition to experience more anxiety symptoms to also perceive others to be more vulnerable to COVID infections in the network analyses for both behaviour classes. This concurring association on within-and between-person levels could reflect a hierarchical structure by which person-level anxiety influences specific situational risk perceptions (e.g., [50]).

In the *within-person lagged* (temporal) analyses, we found no lagged relationships between nodes in the risk cognitions and mental health networks apart from a positive association between depressive symptoms on any day and vulnerability (social distancing) or susceptibility (hygiene) on the following day. As both the mental health and risk cognitions networks were relatively stable over time (i.e., high autocorrelations and low lagged correlations), this is perhaps not surprising and could probably be interpreted in line with the between-person associations discussed above.

Risk perceptions and adherence

In all analyses and for both classes of behaviour, we found consistent associations between risk cognitions and adherence behaviour such that higher levels of perceived behavioural control were associated with higher adherence. *Within-person contemporaneous* analyses show that perceptions of control were associated with lower susceptibility. This could indicate that adherence serves as a means to reduce feeling at risk of infection; at the same time, the evidence on such effects is mixed [51, 52]. Both the control-adherence and risk perception-adherence relationships are in line with assumptions from health behaviour theory - for example, the Health Belief Model [15] and Protection Motivation Theory [16] both propose that individuals engage in protective behaviours in order to mitigate high perceptions of vulnerability and susceptibility if they perceive sufficient control or self-efficacy. Previous COVID-related studies (e.g., [13, 14]) support such relationships, albeit in much lower temporal resolution.

In *within-person lagged analyses*, we found for both distancing and hygiene behaviours that higher vulnerability (self) on any day was associated with higher vulnerability (other) on the next day, and higher vulnerability (other) on any day was associated with higher vulnerability (self) on the following day. Similar patterns were observed between vulnerability (self) and susceptibility. One possible explanation for this pattern is the highly contagious nature of the pandemic and the increased likelihood of infections in social settings. Perceiving oneself to be at risk for infection would imply that others - here, we asked about “friends and family” would be at risk as well, as intra-family and intra-social-network-infections constitute one of the main routes of infections (e.g., [53]).

Limitations

There are some limitations to the interpretation of data in this study. First, all findings have to be interpreted within the context of the assumptions of the underlying models. Specifically, we interpreted lag-associations as an influence of variables on any day on the respective other variable in the next day. This relies on the assumption that such lagged linear associations can be meaningfully interpreted as temporal [54], whereas an alternative explanation for the lack of lagged association could be that the underlying associations are curvilinear or could vary with time (e.g., [49]). Second, as the sample of individuals in the study is self-selected, their levels of being affected through the COVID pandemic and the regulatory measures might differ from the general population. In spite of the relatively high effort involved in completing the study and high drop-out immediately after registering for the study, participants with a past diagnosis of mental illness were more likely to provide enough completed assessments to be included in the analyses. This is in stark contrast with previous research (e.g., [55]). Third, in order to accommodate the possibility that behavioural recommendations change and to cover the range of different imposed measures (maximum of 22 measures in effect nationwide; [56]) during the course of the study, and to try to reduce participant burden, we assessed self-reported adherence as adherence to behavioural domains (hygiene/social distancing) rather than separate behaviours (e.g., hand hygiene vs. mask wearing). In particular hand hygiene and mask wearing have very different implications in that hand hygiene might be both less inconvenient and less overtly visible compared to mask wearing, and thus have less social and political connotations [57]. These differences in turn could suggest that these behaviours are driven by different psychosocial determinants [58].

Assessing behaviours this way prevented us from analysing these behaviours separately, and could have obfuscated differential patterns of associations between behaviours and mental health as well as behavioural determinants. However, previous studies (e.g.,[37]) show that these behaviours do cluster within-person, suggesting that this approach might be suited to capture adherence. Lastly, as with many studies using ecological momentary assessment, data are self-reports and despite the dynamic temporal network analyses, essentially reflect correlations.

Strengths

The study also has a number of strengths, in particular the fact that we were able to assess participants over a relatively long period of time (6 months) with intermittent bouts of intensive longitudinal data assessments. We used validated questionnaires where possible, and were able to retain a substantial proportion of our sample through the course of the study. The decidedly within-person perspective of the study is an asset, as most theories in mental health describe within-person processes, but are rarely tested in studies with sufficient time frames to observe such developments. In addition, by specifying networks between NPI adherence, risk perceptions and mental health indicators for two different behavioural domains, we were able to examine differential associations between mental health, risk perceptions, and adherence behaviours.

Implications and conclusion

To understand the impact of an ongoing pandemic on mental health, risk perception, control beliefs, and adherence to recommended behaviours, it is crucial to identify the temporal dynamics involved in the relationships between these variables. Our study suggests no negative impact of adherence on mental health or vice versa, rather the opposite: Higher adherence to distancing and hygiene recommendations on any given day was associated with better mental health the following day. At the same time, we found plausible and interpretable contemporaneous as well as between-person associations between risk perceptions and control beliefs with adherence, which suggests that individuals can engage in adherence behaviours in order to mitigate subjective experiences of being at risk, if they feel capable of doing so. This implies that interventions need to outline how adhering to recommendations mitigates risk - and policies need to provide individuals with the means to do so. Adherence under such circumstances might consequentially be less detrimental to mental health than previously assumed. At the same time, more research on such associations is needed to establish causality and boundary conditions.

The consistent associations between anxiety and risk perceptions in our study might suggest that measures to reduce individual COVID-related risks might also improve anxiety levels. Most importantly however, we found that poor mental health is unlikely to be a risk factor involved in adherence to recommended COVID mitigation behaviours, and that, at the same time, adherence to such recommended behaviours might be less likely to negatively impact mental health than previously thought - at least if not accompanied by loneliness.

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Table 1

Means, standard deviations, skew and kurtosis for all variables included in the analyses

	M	*SD*	*Skew*	*Kurtosis*
Anxiety symptoms	28.29	25.72	0.83	-0.23
Depression symptoms	30.69	26.27	0.70	-0.47
Dysregulation symptoms	26.44	25.02	0.82	-0.32
Loneliness	28.18	30.28	0.82	-0.63
Adherence (distance)	82.66	26.83	-1.81	2.33
Adherence (hygiene)	88.06	22.65	-2.60	6.45
Perceived behavioral control (distance)	18.92	27.32	1.54	1.21
Perceived behavioral control (hygiene)	15.52	26.01	1.99	3.02
Susceptibility	34.36	31.45	0.59	-0.95
Severity	43.59	28.62	0.27	-1.03
Vulnerability (self)	36.62	29.97	0.43	-1.09
Vulnerability (others)	46.99	33.35	0.05	-1.39

Figure 1. Example for sampling scheme with five-day bouts within months, and with multiple daily assessments (R = Random Assessment; ER = Evening Report) within days.

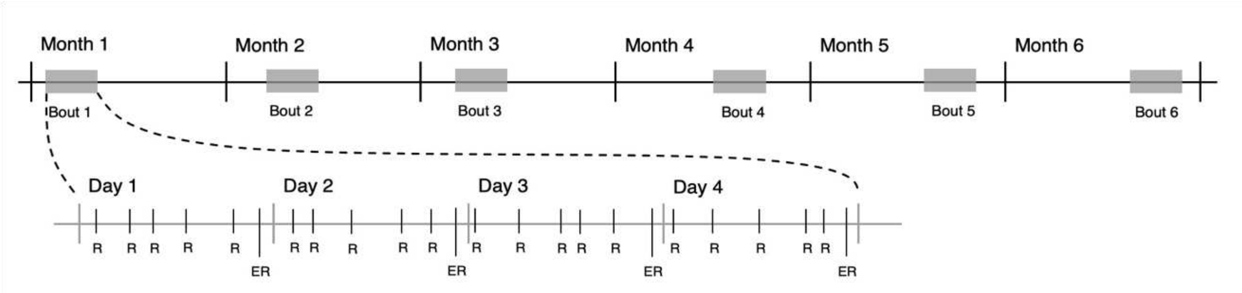
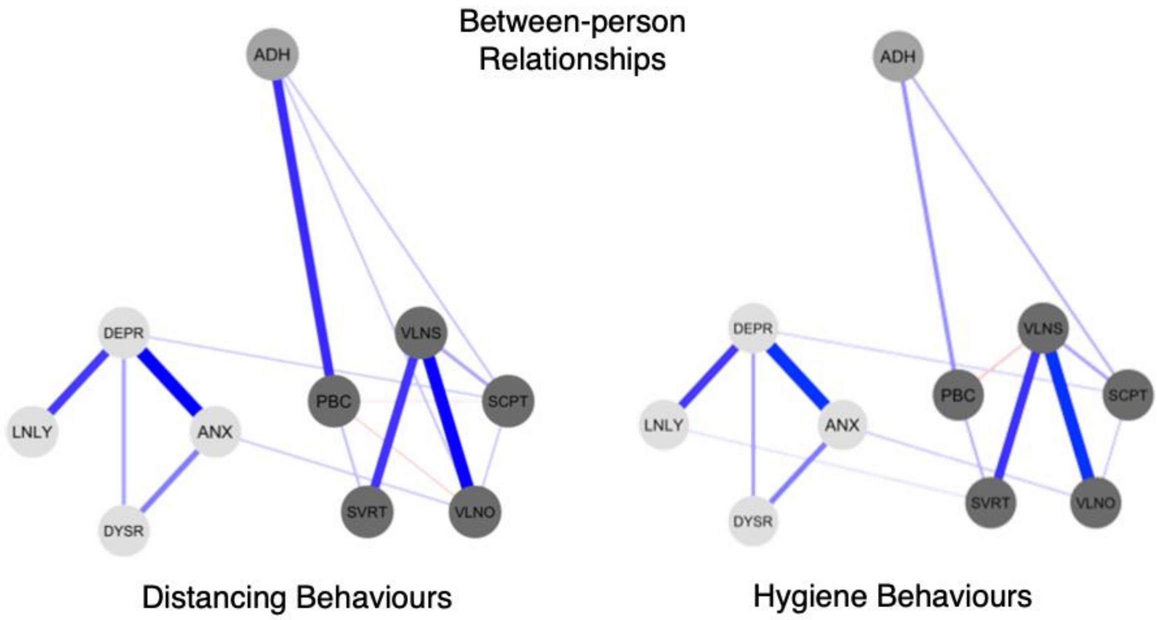
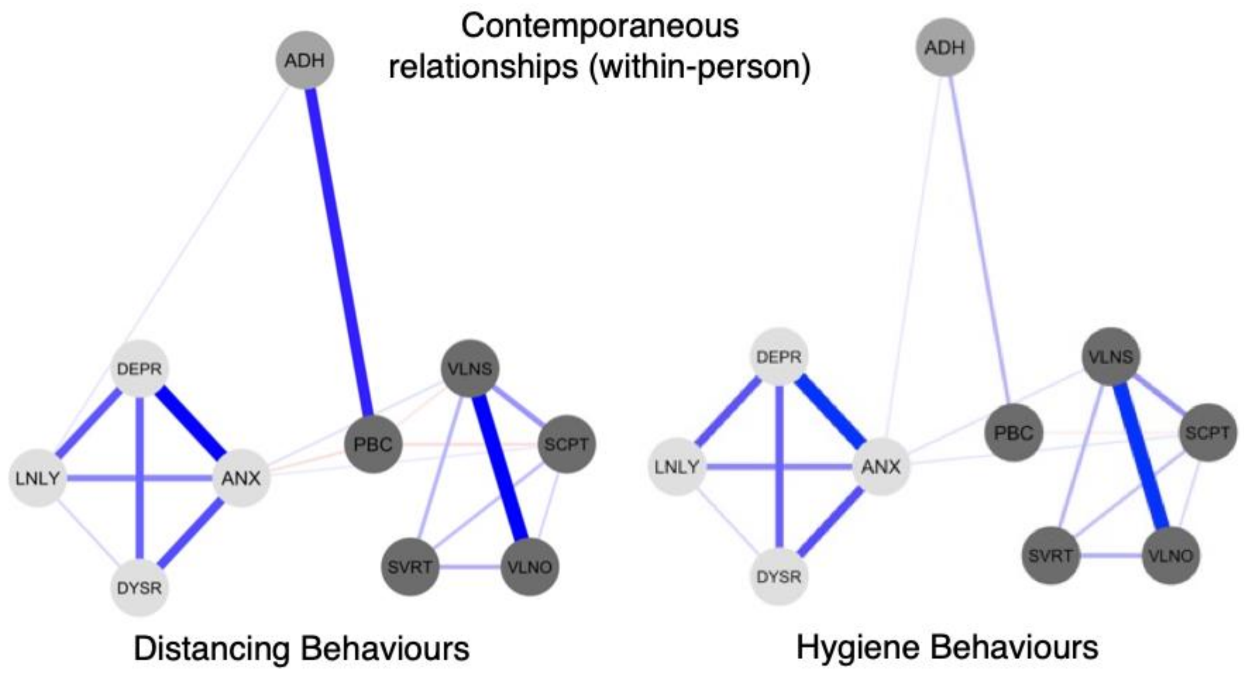


Figure 2. Between-person relationships (edges) for distancing behaviours and hygiene behaviours.



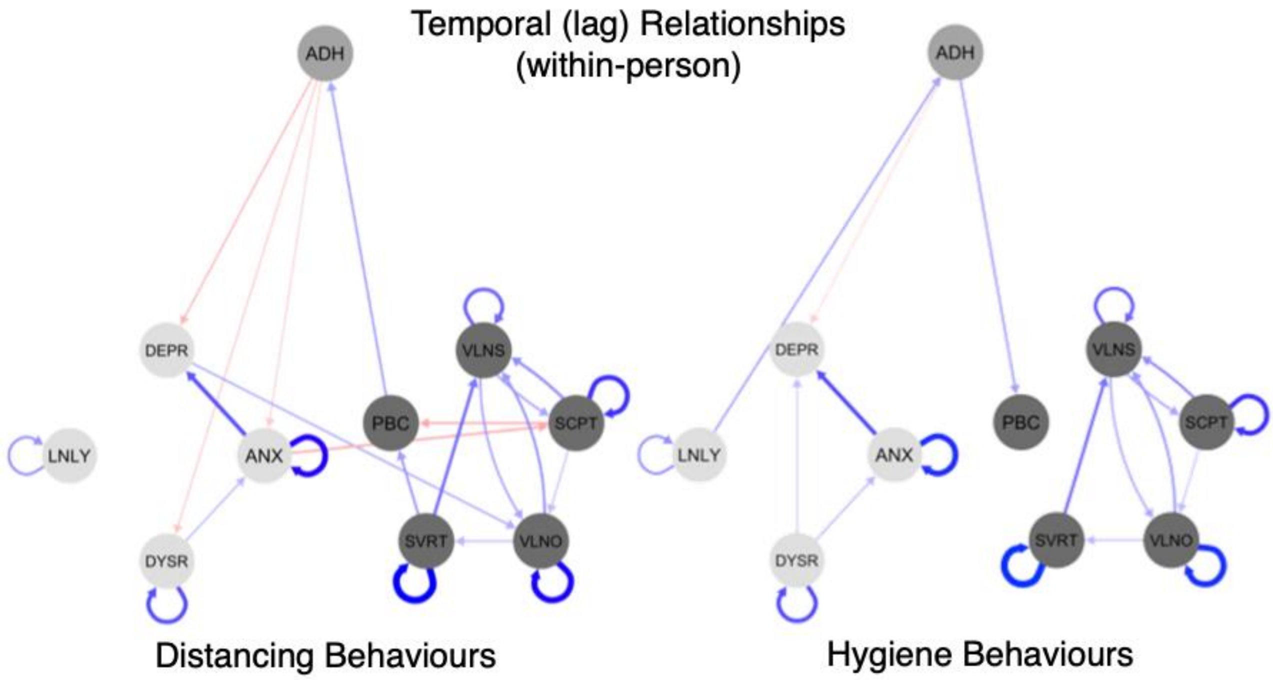
Note. Positive associations (blue), negative associations (red). Line thickness indicates association strength. ADH = Adherence; Mental health indicators: DEPR = Depressive symptoms, LNLY = Loneliness, DYSR = Dysregulation symptoms, ANX = Anxiety symptoms; Cognitions: VLNS = Vulnerability (self), PBC = Perceived behavioural control, SVRT = Severity, VLNO = Vulnerability (others), SCPT = Susceptibility

Figure 3: Contemporaneous relationships (within-person) for distancing behaviours and hygiene behaviours.



Note. Positive associations (blue), negative associations (red). Line thickness indicates association strength. ADH = Adherence; Mental health indicators: DEPR = Depressive symptoms, LNLY = Loneliness, DYSR = Dysregulation symptoms, ANX = Anxiety symptoms; Cognitions: VLNS = Vulnerability (self), PBC = Perceived behavioural control, SVRT = Severity, VLNO = Vulnerability (others), SCPT = Susceptibility

Figure 4: Temporal (lagged) within-person relationships for distancing behaviours and hygiene behaviours



Note. Positive associations (blue), negative associations (red). Line thickness indicates association strength. ADH = Adherence; Mental health indicators: DEPR = Depressive symptoms, LNLY = Loneliness, DYSR = Dysregulation symptoms, ANX = Anxiety symptoms; Cognitions: VLNS = Vulnerability (self), PBC = Perceived behavioural control, SVRT = Severity, VLNO = Vulnerability (others), SCPT = Susceptibility