Journal of Epidemiology and Global Health

‘Dances with Viruses’: The Association between Motivation for COVID-safe Behavior and Epidemiology of COVID-19

--Manuscript Draft--

Manuscript Number:	EPGH-D-22-00151
Full Title:	‘Dances with Viruses’: The Association between Motivation for COVID-safe Behavior and Epidemiology of COVID-19
Article Type:	Research Article
Funding Information:	
Abstract:	Background. To manage the COVID-19 pandemic, governments imposed invasive behavioral measures to limit virus circulation. Because adherence to such measures depends on people’s motivation to comply, the current study investigated the association between daily variation in people’s motivation to adhere to behavioral measures with growth rates of infections and hospitalizations in [blinded for review]. Methods. The data were collected during the first 12 months of the COVID-19 crisis (N = 183,766; 7.2% missing days; 0% vaccinated; Mage = 50.41; 68.2% female). Results. Controlling for a set of pandemic-related covariates and accounting for a lag between infections and hospitalization numbers, a cross-lagged structural equation model revealed significant indirect associations, with increasing infection rates resulting in higher levels of motivation on the same day which, in turn, related to decreasing infections and hospitalizations 43 and 50 days later, respectively. Furthermore, the growth rate in hospitalization numbers was negatively related to motivation and infections after 43 days, which indicated that a reduction of hospitalizations was followed by increasing infection rates and more motivation to comply to the measures after 43 days. Interpretation. These associations highlight the role of motivation as a critical target to develop a preventive policy to change the epidemiological course.
Corresponding Author:	Joachim Waterschoot Ghent University: Universiteit Gent BELGIUM
Corresponding Author E-Mail:	joachim.waterschoot@ugent.be
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	Ghent University: Universiteit Gent
Corresponding Author's Secondary Institution:	
First Author:	Joachim Waterschoot
First Author Secondary Information:	
Order of Authors:	Joachim Waterschoot
	Sofie Morbee
	Vincent Yzerbyt
	Omer Van den Bergh
	Olivier Klein
	Olivier Luminet
	mathias Schmitz
	Pascaline Van Oost
	Maarten Vansteenkiste

Order of Authors Secondary Information:	
Opposed Reviewers:	
Additional Information:	
Question	**Response**
Is this study a clinical trial?<p><i>A clinical trial is defined by the World Health Organisation as ‘any research study that prospectively assigns human participants or groups of humans to one or more health-related interventions to evaluate the effects on health outcomes’.</i>	No

‘Dances with Viruses’:

The Association between Motivation for COVID-safe Behavior and Epidemiology of COVID-19

Joachim Waterschoot*[a] (Drs)

Sofie Morbée[a] (Drs)

Vincent Yzerbyt[c] (Prof)

Omer Van den Bergh[b] (Prof)

Olivier Klein[d] (Prof)

Olivier Luminet[c, e] (Prof)

Mathias Schmitz[c] (Doctor)

Pascaline Van Oost[c] (Drs)

Maarten Vansteenkiste[a] (Prof)

[a] Department of Developmental, Personality and Social Psychology. Ghent University, Ghent, Belgium.

[b] Health Psychology, Faculty of Psychology and Educational Sciences. University of Leuven, Leuven, Belgium.

[c] Institute for Research in the Psychological Sciences. Université Catholique de Louvain, Louvain-la-Neuve, Belgium.

[d] Center for Social and Cultural Psychology (CeSCuP), Faculty of Psychological Sciences and Education. Université libre de Bruxelles, Bruxelles, Belgium.

[e] Fund for Scientific Research (FRS-FNRS), Brussels, Belgium

[*] Corresponding author: Joachim Waterschoot, Faculty of Psychology, Department of Developmental, Personality, and Social Psychology, Henri Dunantlaan 2, B-9000, Ghent, Belgium. E-mail: Joachim.Waterschoot@ugent.be, Tel. + 09 264 62 70, http://orcid.org/0000-0003-0845-9310

Abstract

Background. To manage the COVID-19 pandemic, governments imposed invasive behavioral measures to limit virus circulation. Because adherence to such measures depends on people's motivation to comply, the current study investigated the association between daily variation in people's motivation to adhere to behavioral measures with growth rates of infections and hospitalizations in [blinded for review].

Methods. The data were collected during the first 12 months of the COVID-19 crisis (N = 183,766; 7.2% missing days; 0% vaccinated; *M*age = 50.41; 68.2% female).

Results. Controlling for a set of pandemic-related covariates and accounting for a lag between infections and hospitalization numbers, a cross-lagged structural equation model revealed significant indirect associations, with increasing infection rates resulting in higher levels of motivation on the same day which, in turn, related to decreasing infections and hospitalizations 43 and 50 days later, respectively. Furthermore, the growth rate in hospitalization numbers was negatively related to motivation and infections after 43 days, which indicated that a reduction of hospitalizations was followed by increasing infection rates and more motivation to comply to the measures after 43 days.

Interpretation. These associations highlight the role of motivation as a critical target to develop a preventive policy to change the epidemiological course.

Keywords: motivation, COVID-19, infections, hospitalizations, health behaviors

Introduction

The sudden emergence of the COVID-19 pandemic challenged the global population in an important number of ways. To increase protection from infection [4] and to keep the pandemic under control [15], people of most countries were asked to adhere to a range of behavioral measures, such as physical distancing, wearing face masks, and restricting social contacts. People generally proved sensitive to these measures. Indeed, when there was greater virus circulation, less public transport and traffic was detected [7] and self-reported surveys showed increased mask wearing [21] and more restricted social contact behavior [8]. In fact, behavior change took place even before the government had imposed these protective measures, suggesting the role of personal motivations to stay safe [9].

Using the framework of Self-Determination Theory (SDT) [23], the present study focusses on the role of autonomous motivation to adhere to behavioral measures to help controlling the pandemic. When autonomous motivation is high, people consider the behavioral measures as necessary, relevant, and congruent with their personal values (e.g., solidarity, health). If this is the case, adherence to the behavioral measures is less driven by external pressures, such as avoiding criticism and sanctions. Compared to external pressure, autonomous motivation has been shown to carry more solid predictive validity for people’s sustained engagement in COVID-safe behavior [16, 17, 27].

However, no studies so far have examined the association between autonomous motivation for behavioral measures on the one hand and the incidence of key epidemiological parameters, such as infections and hospitalizations, on the other. Establishing such an association is important because autonomous motivation is an antecedent of actual behavior, implying that a proper monitoring of motivation should allow to anticipate epidemiological changes earlier in time. In the present study, we examined the between-day associations between motivation and changes in concurrent (i.e., on the same day) and prospective (i.e., time-lagged) daily infection and hospitalization numbers. At the concurrent level, we expected increases (decreases) in infections and hospitalizations to related with higher (lower) levels of motivation. For instance, a higher prevalence of infections and hospitalizations signals higher health risks, which may be expected to reinforce the perceived necessity and relevance of the behavioral measures, thereby increasing autonomous motivation. To be sure, this positive association at the concurrent level may change as time passes by, and even become negative. Indeed, keeping with the example, higher motivation will come with lower virus circulation through increased adherence to behavioral measures, resulting in lower infections and lower hospitalizations later. As such, this situation would then materialize in lower motivation at the concurrent level. In sum, as far as a prospective association is concerned, we expected a negative association with higher (lower) levels of motivation at one point in time being related to a lower (higher) incidence of infections and hospitalizations weeks later.

Regarding the prospective association, we did not formulate hypotheses about the exact time lag between motivational changes and changes of the epidemiological situation. Before people's behavior influences infection rates in a measurable way, several intervals of variable time length ought to be taken into account, such as those related to the exponential steepness of the virus spreading, time to symptom onset (4-6 days), the performance of tests and the reception of results (0.5 – 1 week), and the registration policy of cases [3, 5, 6, 13, 19, 29]. Moreover, to shed light on the unique importance of motivational differences, we also included a broad set of relevant pandemic-related covariates (i.e., stringency of the sanitary behaviors, weather, holiday periods, crisis periods, duration of the crisis, and weekend period).

Methods

Study design and Sample

We collected the data in the context of a national research project in [blinded for review]., called [blinded for review]. We distributed an online survey through social media, societal organizations and the press on a regular basis. The research project aimed to monitor psychological aspects of the COVID-19 pandemic in the [blinded for review] population and obtained ethical approval from the Ethics Committee of [blinded for review]. At both the beginning and the end of the questionnaire, we provided contact information (e.g., information websites, email address) in case of unclarities or in case the questionnaire had provoked negative thoughts and feelings.

For the current research, we included participants living in Flanders who had participated in the study during the first 12 months of the crisis, that is, from 19th of April 2020 to 19th of April 2021 (N = 183,766 participants; M_{age} = 50.41; 68.2% female; 0% vaccinated participants). We limited the time window because the vaccination campaign was rolled out at a fast pace after April 19th 2021, thereby impacting people's motivation and the epidemiological situation. Overall, 340 days of data collection took place, with a maximum gap of three days between consecutive days of data collection. On average, 660 participants filled out the questionnaire on a given day, with more than 100 participants participating in 92.8% of the days.

Materials

Motivation to engage in COVID-safe behaviors

We assessed people's motivation to adhere to behavioral sanitary measures that were either legally required or strongly recommended by policymakers using adapted versions of the Behavioral Regulation in

Sport Questionnaire [17] and the Environmental Amotivation Scale [18]. Following the stem "Over the past week, I've adhered to these sanitary behaviors because…", people answered 4 items assessing autonomous motivation (e.g., "… I find it personally relevant.", $\alpha = .89$) and 4 items assessing controlled motivation (e.g., "… I feel pressured to do this.", $\alpha = .81$). All items were to be rated on a 5-point Likert scale ranging from 1 (totally disagree) to 5 (totally agree). To end up with one score of motivation representing the level of one's relative autonomous motivation, a difference score was calculated with controlled motivation being subtracted from autonomous motivation.

Growth rates in COVID-19 numbers

We obtained data on infections and hospitalizations from Sciensano, the national public health institute of [blinded for review] [26]. We represented the epidemiological situation by calculating changes (percent) in both infection numbers and hospitalizations. This was done by calculating percentages of change in increment curve values, according to the following formula $(c1-c0)/c0$ in which $c1$ is the number of infections in the last 7 days and $c0$ is the number of infections in the 7 days before. The changes represent increasing (> 0%), decreasing (< 0%) or stable (0%, at a peak or valley) absolute numbers. This approach averages out the impact of weekends on data collection (during weekends, there was less data collection). Also, it allows to rely on linear modeling in the analyses while the raw numbers would need an approach using Poisson models, resulting in more difficult calculations and interpretations.

Pandemic-related covariates

Periods in the pandemic. Percent changes across the different phases of the pandemic are non-stationary, indicating that fluctuations do not show a recurrent pattern across time (*Dickey-Fuller test* (7) = -2.83, p=.22). To control for these differences in the analyses and to make sure that our associations are relevant to all fluctuations across the pandemic, we performed a procedure to identify which epidemiological trends are significant. To do this, we used a non-parametric smoothing technique (i.e., Generalized Additive Model procedure; GAM ; 11) to establish the main trajectories in both the infection and hospitalization changes across time, thereby estimating a particular number of splines (i.e., a polynomial regression line) between significant moments in time (i.e., knots) with zero slopes, i.e., a valley (i.e., local minimum) or a peak (i.e., local maximum). After model fitting, we checked model assumptions and the general model performance by comparing the estimated degrees of freedom (EDF) with the maximum dimension of spline functions (*k'*; see table S1). The result showed a total number of 15 infections-related periods (N_{range}= 13 – 31 days) and 15 hospitalizations-related periods (N_{range}= 12 – 47 days), each including a significant trend in the percent changes up- or downwards (see figure S1).

Weekends and holidays. To control for the impact of weekend days [24] and of holiday periods [1], we included two dichotomous variables, namely Type of Day (weekdays = 0; weekend days = 1) and Holiday period (yes = 1; no = 0).

Stringency of the sanitary behaviors. Because the pandemic was characterized by successive waves, the government imposed stricter sanitary behaviors (e.g., closure of schools, travel restrictions, strong limitations of social contact, etc.) during some periods and relaxed these sanitary behaviors during other periods. Hale et al. [10] tracked the strictness of these rules and generated the Oxford COVID-19 Government Response Tracker (OxCGRT). OxCGRT provides a percentage representing the level of stringency of restrictions across time. We used this measure in our study to operationalize the strictness of different sanitary behaviors across the crisis. In general, studies have shown that the impact of governmental restrictions on the COVID-19 metrics emerged around the 9th day after their implementation [19].

Weather. We used the data of the Royal Meteorological Institute of [blinded for review]. ([abbreviation and link are blinded for review].) to control for weather indicators across the pandemic. We did this because studies [14] showed that the weather influences the number of infections, with cold and dry conditions facilitating virus spreading, in part because people spend more time inside. Specifically, we included daily temperature (in degrees Celsius) and sunshine duration (in minutes).

Plan of Data Analysis

We quantified the synchrony between measures of motivation and the COVID-19 growth rates in a concurrent and a prospective way. Given the small number of missing days (7.3%) and small gaps (3 days at max), we imputed this data by the linear interpolation algorithm, including time dependencies.

In a first step, we examined Pearson correlations to inspect concurrent as well as prospective, i.e., time-lagged, associations. As the latter was exploratory, we used a lag of 60 days to capture most of the epidemiological intervals. The time lag showing the strongest associations was used for the Cross-Lagged Structural Equation Modeling (CL-SEM)[1]. Herein, we included both autoregressive and cross-lagged pathways, thereby controlling for a set of covariates. In this model, we included both growth rates of infections and

[1] Initially, we planned to repeat this procedure in four different regions in Flanders who had a sufficient amount of data on a daily base, doing this to demonstrate internal replication of the findings. However, with ‘region’ as a second level, the intra-class correlation (ICC) showed a value of 0.005 for between-region variance, indicating no significant amount of variance. Therefore, we decided to use all available data in Flanders, allowing us to use a minimum of 100 participants per day.

hospitalizations to account for an indirect sequence going from motivation to infections to hospitalizations and to check whether the association between motivation and hospitalizations later in time would be explained by its association with the infection numbers earlier in time. Given the size of the current dataset, we achieved approximately 95% power in a SEM including an effect size of 0.80 (Richard et al., 2003) and a general correlation structure.

Results

Table 1 presents the Pearson correlations with descriptive statistics, showing that motivation is positively correlated with growth rates in infections, while being unrelated to growth rates in hospitalizations on the same day. This indicates that when the epidemiological situation was worrying (i.e., slowdown in decreasing numbers or increasing numbers), the levels of motivation were higher. Further, the negative correlation between the duration of the pandemic and motivation shows that motivation decreased across time, probably because of 'pandemic fatigue' [20]. The stringency index shows negative correlations with growth rates of infections and hospitalizations. Indeed, stricter sanitary behaviors were launched on moments of negative evolutions, i.e., when the absolute numbers were high, and the increase already started to slow down or started to decrease after a peak. The stringency index was only minimally negatively related with autonomous motivation, suggesting that more stringent measures do not necessarily come with lowered motivation.

Time-lagged cross-correlations are visualized in figure 1, showing sinusoidal patterns. In line with the literature, growth rates of infections are strongly positively related to growth rates of hospitalizations 10 days later. Further, a decreasing pattern for motivation emerges, with strongest correlations for growth rates in infections located at a lag of 43 days, and for growth rates of hospitalizations at a lag of 50 days.

Based on these results, we included three time lags in the CL-SEM (i.e., day x, day x+43 and day x+50) to capture both the concurrent and the two prospective associations. Additionally, we controlled each pathway for the set of pandemic-related covariates. The output can be found in Table 2, while Figure 2 visualizes all significant pathways. Herein, this model presents standardized coefficients, showing significant direct associations between motivation and growth rates in infections and hospitalizations 43 and 50 days later, respectively. Interestingly, a significant indirect effect is found with, for instance, lower motivation at day x resulting in higher growth rates of infections 43 days later and, subsequently, resulting in positive growth rates of hospitalizations 7 days later ($\beta_{indirect}$=-.25, p<.001). Also, the 7-day lag shows a significant association between the growth rates of infections and motivation one week later, while the reverse pattern is not significant. Finally, unique negative associations are found between the growth rates in hospitalizations and both motivation and growth rates in infection numbers, indicating that when hospitalizations rates were decreasing, the infection rates and levels of motivation were increasing again 43 days later.

Discussion

During the first year of the COVID-19 pandemic, most governments imposed a panoply of behavioral sanitary measures (e.g., restricting social contact) to prevent the dissemination of the virus. Autonomous motivation, which reflects voluntary endorsement of the necessity and value of such measures, is an important and reliable predictor of actual compliance [17]. Because motivation typically precedes actual behavior which, in turn, precedes changes in the epidemiological situation, we investigated whether changes in autonomous motivation predict changes in critical epidemiological parameters, and at which time lag this association would be strongest.

Using a large dataset, our study is the first to show that variation in daily autonomous motivation is negatively related to changes in infection rates 43 days later, and to changes in hospitalizations one week thereafter. This association was fairly strong in terms of standardized coefficients and proved to be robust, even after controlling for variations in the imposed sanitary measures (i.e., stringency index) and other pandemic-related covariates, such as the weather and holiday periods (e.g., Majumder & Ray, 2021). Interestingly, our findings also show that daily levels of autonomous motivation were positively associated with changes in infection rates on the same day, suggesting that increasing infection rates - as communicated by the authorities and the media - predict more autonomous motivation to comply to the behavioral measures [16, 17]. The current findings are in line with previous work across different countries, showing that people spontaneously adapt their social behavior and report more face masks use, even before governments imposed behavioral sanitary measures [9].

On average, cross-correlations for all types of motivation were strongest on time lags of 43 days for infections rates and then 7 days later for hospitalizations rates, i.e., after 50 days. Interestingly, this difference matches earlier literature showing the effects of infection numbers represented in the hospitalization numbers between 7 and 13 days later [5]. Different mechanisms may account for the length of the observed time lags, like the incubation period of 4-6 days or the time interval between the first appearance of symptoms and visit to a doctor, the actual testing, and an official registration [29]. Also consider the time delay to acquire test results, allowing people to inadvertently infect each other [25]. Because of its high contagiousness, the virus propagated exponentially across the population such that the number of new daily infections doubled on average within 3 days at the peak of the COVID-19 outbreak during the period of the current study [2, 20].

As a well-known concept in complex, dynamic systems, the current findings definitely point to the existence of a negative feedback loop, with the epidemiological situation impacting people's motivation and behavior, which in turn impact the epidemiological situation. From a practical point of view, policy makers could use strategies to enhance people's sustainable motivation to alter or to break down this loop, even in periods of decreasing numbers and low virus circulation. For instance, this could be done by communicating more decidedly about different prospective scenarios so as to show the consequences of people's behavior (i.e., 'if-then' scenarios).

Limitations and Future Directions

A number of limitations need to be formulated. Despite the high number of participants, the results are not representative of the entire population of [blinded for review]. The main reason for this is that participation is based on the respondent's decision, resulting in *self-selection*. This self-selection can be driven by situational, psychological, or sociodemographic elements. For example, respondents might have a computer, tablet or smartphone and internet connection, with an interest in (aspects of) COVID-19 policy, with motivation to complete the list, with a particular conviction for or against certain sanitary behaviors, with an understanding of the questions posed, etc. This self-selection was corrected to some extent through statistical methods (e.g., adding weights to the dataset). However, we did not include these weights in the current study, because of biases in parameter estimations depending on the type of statistical weighting approaches [30].

Second, we did not directly compare the predictive capacity of this psychologically-based and motivational model to more traditional epidemiological models, in order to assess whether adding motivation would improve traditional models. Future research could include the measurements of motivation into the construction of predictive models regarding the COVID-19 pandemic [5]. Earlier efforts showed that such models, which are mainly based on the registered COVID-19 numbers itself, provide predictions between 5 and 40 days [12]. However, like in the present research, the predictive validity of such models decreases when the time lag increases. Since motivation is a crucial psychological antecedent of people's behavior, it remains an important empirical question whether and to what extent the inclusion of motivation would enhance the predictive power of epidemiological models.

Third, other covariates might be taken into account in the association of motivation with the COVID-19 numbers, such as the proportion of vaccinated people or people's level of risk perception which may depend on specific types of COVID-19 variants.

Conclusions

The current findings showed a remarkable “dance”, indeed a feedback loop, between people’s motivation for behavioral measures and critical COVID-19 epidemiological parameters. Increases in infections on a given day relate to higher levels of autonomous motivation to adhere the sanitary behaviors on that day. This higher level of motivation results in a more positive epidemiological situation later in time which, in turn, induces a decline in autonomous motivation for behavioral measures and, thus, more virus spreading and increasing COVID-19 infections. Policymakers may greatly benefit from a close monitoring of motivational changes because this would allow to anticipate epidemiological changes way ahead. In addition, inducing autonomous motivation for behavioral measures through appropriate communication strategies would allow policymakers to lead the dance and eventually reduce the number of infections, hospitalizations, and deaths.

List of Abbreviations

- SDT= Self-Determination Theory
- GAM = Generalized Additive Model procedure
- EDF = estimated degrees of freedom
- OxCGRT = Oxford COVID-19 Government Response Tracker
- CL-SEM = Cross-Lagged Structural Equation Modeling

Declarations

Ethics approval and consent to participate

The present research was financially supported by the [blinded] Federal Ministry of Health through RIZIV (Rijksinstituut voor ziekte- en invaliditeitsverzekering) / INAMI (institut national de maladie-invalidité). The funders of the study played no role in study design, data collection, data analysis, data interpretation, or writing of the manuscript. Also, the authors declare that they have no personal or financial conflict of interest that could have influenced the work reported in this paper.

This research does not contain any studies with animals performed by any of the authors. All procedures performed in studies involving human participants were accepted by the Ethical Committee of [blinded]. All procedures were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

Consent for publication

Not applicable

Availability of data and material

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all sanitary behaviors in the study, and we follow JARS. All data, analysis code, and research materials are available at https://osf.io/5cdj7/?view_only=c8de645ab8eb4eb8b5eb613367fde362. Datasets are hosted in Zenodo (a public repository) and are available upon request and for replication purposes only: https://doi.org/10.5281/zenodo.5749193. We analyzed the data using R, version 4.1.2. The study was not preregistered.

Competing interests

The authors declare that they have no personal or financial conflict of interest that could have influenced the work reported in this paper.

Funding

The present research was financially supported by the [blinded] Federal Ministry of Health through 36 RIZIV (Rijksinstituut voor ziekte- en invaliditeitsverzekering) / INAMI (institut national de maladie-invalidité)

Authors' contributions

JW carried out the conceptualization, data curation, formal analysis, investigation, methodology, resources, software, visualization and writing (original draft, review and editing). SM carried out the conceptualization, data curation, investigation, methodology and writing (original draft, review and editing). VY carried out the conceptualization, the formal analysis, the funding acquisition, the investigation, the methodology, the project administration, the supervision, the validation and the writing (original draft, review and editing). PVO carried out the conceptualization and the writing (original draft, review and editing). OK carried out the conceptualization, the formal analysis, the funding acquisition, the investigation, the methodology, the project administration, the supervision, the validation and the writing (original draft, review and editing). OL carried out the conceptualization, the formal analysis, the funding acquisition, the investigation, the methodology, the project administration, the supervision, the validation and the writing (original draft, review and editing). MS carried out the conceptualization and the writing (original draft, review and editing). OvDB carried out the conceptualization, the data curation, the formal analysis, the funding acquisition, the investigation, the methodology, the project administration, the resources, the software, the supervision, the validation and the writing (original draft, review and editing). MV carried out the conceptualization, the data curation, the formal analysis, the funding acquisition, the investigation, the methodology, the project administration, the resources, the software, the supervision, the validation, the visualization and the writing (original draft, review and editing). All authors read and approved the final manuscript.

Acknowledgements

The Motivation Barometer was initiated by [blinded] during the first lockdown with scholars from the 45 [blinded], [blinded] and [blinded] joining the project along the way. Throughout the course of the pandemic, data collection was made possible from [blinded] and the Ministry of Health to the 47 consortium of universities. The Ethics Committee of [blinded] approved the project.

References

1. Chen, S., Chen, Q., Yang, W., Xue, L., Liu, Y., Yang, J., Wang, C., & Bärnighausen, T. (2020). Buying time for an effective epidemic response: The impact of a public holiday for outbreak control on COVID-19 epidemic spread. *Engineering*, *6*(10), 1108-1114. https://doi.org/10.1016/j.eng.2020.07.018
2. Coletti, P., Libin, P., Petrof, O., Willem, L., Abrams, S., Herzog, S. A., ... & Hens, N. (2021). A data-driven metapopulation model for the Belgian COVID-19 epidemic: Assessing the impact of lockdown and exit strategies. *BMC infectious diseases*, *21*(1), 1-12.
3. Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong Social Distancing Sanitary behaviors In The United States Reduced The COVID-19 Growth Rate: Study evaluates the impact of social distancing sanitary behaviors on the growth rate of confirmed COVID-19 cases across the United States. *Health affairs*, *39*(7), 1237-1246.
4. Doung-Ngern, P., Suphanchaimat, R., Panjangampatthana, A., Janekrongtham, C., Ruampoom, D., Daochaeng, N., ... & Limmathurotsakul, D. (2020). Case-control study of use of personal protective measures and risk for SARS-CoV 2 infection, Thailand. *Emerging infectious diseases*, *26*(11), 2607.
5. Faes, C., Abrams, S., Van Beckhoven, D., Meyfroidt, G., Vlieghe, E., Hens, N., & Belgian Collaborative Group on COVID-19 Hospital Surveillance Belgian Collaborative Group on COVID-19 Hospital Surveillance. (2020). Time between symptom onset, hospitalisation and recovery or death: Statistical analysis of Belgian COVID-19 patients. *International Journal of Environmental Research and Public Health*, *17*(20), 7560. https://doi.org/10.3390/ijerph17207560
6. Jamison, J. C., Bundy, D., Jamison, D. T., Spitz, J., & Verguet, S. (2021). Comparing the impact on COVID- 19 mortality of self- imposed behavior change and of government regulations across 13 countries. *Health services research*, *56*(5), 874-884.
7. García-Cremades, S., Morales-García, J., Hernández-Sanjaime, R., Martínez-España, R., Bueno-Crespo, A., Hernández-Orallo, E., López-Espín, J. J., & Cecilia, J. M. (2021). Improving prediction of COVID-19 evolution by fusing epidemiological and mobility data. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-94696-2
8. Gollwitzer, A., McLoughlin, K., Martel, C., Marshall, J., Höhs, J. M., & Bargh, J. A. (2021). Linking Self-Reported Social Distancing to Real-World Behavior During the COVID-19 Pandemic. *Social Psychological and Personality Science*, 194855062110181. https://doi.org/10.1177/19485506211018132

9. Guan, M., & So, J. (2020). Tailoring temporal message frames to individuals' time orientation strengthens the relationship between risk perception and behavioral intention. *Journal of Health Communication*, *25*(12), 971-981. https://doi.org/10.1080/10810730.2021.1878310

10. Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529-538. https://doi.org/10.1038/s41562-021-01079-8

11. Hastie, T., & Tibshirani, R. (1990). Exploring the nature of covariate effects in the proportional hazards model. *Biometrics*, *46*(4), 1005. https://doi.org/10.2307/2532444

12. Hussein, T., Hammad, M. H., Surakhi, O., AlKhanafseh, M., Fung, P. L., Zaidan, M. A., ... & Ershaidat, N. (2022). Short-Term and Long-Term COVID-19 Pandemic Forecasting Revisited with the Emergence of OMICRON Variant in Jordan. *Vaccines*, *10*(4), 569.

13. Lyu, W., & Wehby, G. L. (2020). Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US: Study examines impact on COVID-19 growth rates associated with state government mandates requiring face mask use in public. *Health affairs*, *39*(8), 1419-1425.

14. Majumder, P., & Ray, P. P. (2021). A systematic review and meta-analysis on correlation of weather with COVID-19. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-90300-9

15. Margraf, J., Brailovskaia, J., & Schneider, S. (2021). Adherence to behavioral Covid-19 mitigation measures strongly predicts mortality. *PLoS One*, *16*(3), e0249392.

16. Martela, F., Hankonen, N., Ryan, R. M., & Vansteenkiste, M. (2021). Motivating voluntary compliance to behavioural restrictions: Self-determination theory-based checklist of principles for COVID-19 and other emergency communications. *European Review of Social Psychology*, *32*(2), 305-347. https://doi.org/10.1080/10463283.2020.1857082

17. Morbée, S., Vermote, B., Waterschoot, J., Dieleman, L., Soenens, B., Van den Bergh, O., Ryan, R. M., Vanhalst, J., De Muynck, G.-J., & Vansteenkiste, M. (2021). Adherence to COVID-19 sanitary behaviors: The critical role of autonomous motivation on a short- and long-term basis. *Motivation Science*. https://doi.org/10.1037/mot0000250

18. Pelletier, L. G., Dion, S., Tuson, K., & Green-Demers, I. (1999). Why do people fail to adopt environmental protective behaviors? Toward a taxonomy of environmental amotivation. *Journal of Applied Social Psychology*, *29*(12), 2481-2504. https://doi.org/10.1111/j.1559-1816.1999.tb00122.x
19. Pellis, L., Scarabel, F., Stage, H. B., Overton, C. E., Chappell, L. H. K., Fearon, E., Bennett, E., Lythgoe, K. A., House, T. A., Hall, I., & University of Manchester COVID-19 Modelling Group. (2021). Challenges in control of COVID-19: short doubling time and long delay to effect of interventions. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1829). https://doi.org/10.1098/rstb.2020.0264
20. Petherick, A., Goldszmidt, R., Andrade, E. B., Furst, R., Hale, T., Pott, A., & Wood, A. (2021). A worldwide assessment of changes in adherence to COVID-19 protective behaviours and hypothesized pandemic fatigue. *Nature Human Behaviour*, *5*(9), 1145-1160. https://doi.org/10.1038/s41562-021-01181-x
21. Rader, B., White, L. F., Burns, M. R., Chen, J., Brilliant, J., Cohen, J., ... & Brownstein, J. S. (2021). Mask-wearing and control of SARS-CoV-2 transmission in the USA: a cross-sectional study. *The Lancet Digital Health*, *3*(3), e148-e157.
22. Richard, F. D., Bond, C. F., Jr., & Stokes-Zoota, J. J. (2003). One hundred years of social psychology quantitatively described. *Review of General Psychology*, *7* (4), 331–363.
23. Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Publications.
24. Ricon-Becker, I., Tarrasch, R., Blinder, P., & Ben-Eliyahu, S. (2020). A seven-day cycle in COVID-19 infection and mortality rates: are inter-generational social interactions on the weekends killing susceptible people? *MedRxiv*, 2020-05.
25. Sah, P., Fitzpatrick, M. C., Zimmer, C. F., Abdollahi, E., Juden-Kelly, L., Moghadas, S. M., Singer, B. H., & Galvani, A. P. (2021). Asymptomatic SARS-CoV-2 infection: A systematic review and meta-analysis. *Proceedings of the National Academy of Sciences*, *118*(34), e2109229118. https://doi.org/10.1073/pnas.2109229118
26. Sciensano. (2021, 20 april). *COVID-19*. https://epistat.wiv-isp.be/covid/
27. Sheeran, P., Wright, C. E., Avishai, A., Villegas, M. E., Rothman, A. J., & Klein, W. M. P. (2021). Does increasing autonomous motivation or perceived competence lead to health behavior change? A meta-analysis. *Health Psychology*, *40*(10), 706716. https://doi.org/10.1037/hea0001111

28. Petersen, M. B., Christiansen, L. E., Bor, A., Lindholt, M. F., Jørgensen, F., Adler-Nissen, R., ... & Lehmann, S. (2022). Communicate hope to motivate the public during the COVID-19 pandemic. *Scientific Reports*, *12*(1), 1-7.

29. Wei, Y., Wei, L., Liu, Y., Huang, L., Shen, S., Zhang, R., ... & Chen, F. (2021). Comprehensive estimation for the length and dispersion of COVID-19 incubation period: A systematic review and meta-analysis. *Infection*, 1-11. https://doi.org/10.1007/s15010-021-01682-x

30. Wood, F., Goldwater, S., & Black, M. J. (2006). A non-parametric Bayesian approach to spike sorting. https://doi.org/10.1109/iembs.2006.260700

31. Wood, S. N., Pya, N., & Säfken, B. (2016). Smoothing parameter and model selection for general smooth models. *Journal of the American Statistical Association*, *111*(516), 1548-1563. https://doi.org/10.1080/01621459.2016.1180986

32. Zhang, Z., & Yuan, K.-H. (2018). *Practical Statistical Power Analysis Using Webpower and R* (Eds). Granger, IN: ISDSA Press.

Table 1. Pearson correlations with Descriptive statistics.

Variable	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.
1. Autonomous motivation	0.45	0.32							
2. Infections	8.74	34.9	.14***						
3. Hospitalizations	2.55	26.04	-.01	.49***					
4. Crisis duration	219	105.51	-.52***	-.04	.20***				
5. Stringency Index	61.37	8.81	-.12*	-.62***	-.33***	.03			
6. Temperature	11.24	6.7	.07	.18***	.04	-.66***	-.22***		
7. Sun duration	296.49	273.81	-.02	-.01	-.15**	-.31***	.19***	.45***	
8. Holiday period	0.29	0.46	-.22***	-.01	.06	-.02	-.07	.24***	.03

*Note. *** p <.001, ** p <. 01, * p < .05; ICV = Increment Curve Values; Under diagonal refers to between-subject correlations; Above diagonal refers to within-subject correlations.*

Table 2. Output of Cross-Lagged Structural Equation Model for motivation, infection and hospitalization growth rates across time.

Outcome	*Predictor*	*Estimate*	*Std. Err.*	*p*	*95%-CI*
Motivation (x + 50)					
	Motivation (x + 43)	**.80**	**0.04**	**<.001*****	[.72; .87]
	Infections (x + 43)	**.11**	**0.04**	**<.001*****	[.09; ..14]
	Hospitalizations (x + 43)	-.08	0.04	.084	[-.16; .01]
	Motivation (x)	**-.10**	**0.05**	**.031***	[-.18; -.08]
	Infections (x)	.03	0.04	.423	[-.05; .11]
	Hospitalizations (x)	.05	0.04	.187	[-.03; .13]
Infections (x + 50)					
	Motivation (x + 43)	.06	0.04	.112	[.04; .20]
	Infections (x + 43)	**.76**	**0.04**	**<.001*****	[.71; .87]
	Hospitalizations (x + 43)	.09	0.04	.08	[.06; .14]
	Motivation (x)	**-.23**	**0.05**	**<.001*****	[-.34; -.16]
	Infections (x)	**.04**	**0.04**	**.008****	[.03; .19]
	Hospitalizations (x)	-.11	0.04	.07	[-.19; .03]
Hospitalizations (x + 50)					
	Motivation (x + 43)	-.04	0.02	.082	[-.08; .02]
	Infections (x + 43)	**.51**	**0.02**	**<.001*****	[.40; .59]
	Hospitalizations (x + 43)	**.59**	**0.02**	**<.001*****	[.53; .63]
	Motivation (x)	**-.15**	**0.03**	**<.001*****	[-.19; -.09]
	Infections (x)	.07	0.02	.07	[-.02; .10]
	Hospitalizations (x)	.01	0.02	.723	[-.04; .05]
Motivation (x + 43)					
	Motivation (x)	**-.34**	**0.05**	**<.001*****	[-.41; -.24]
	Infections (x)	-.09	0.05	.08	[-.18; .01]
	Hospitalizations (x)	**-.36**	**0.04**	**<.001*****	[-.40; -.24]
Infections (x + 43)					
	Motivation (x)	**-.48**	**0.06**	**<.001*****	[-.61; -.36]
	Infections (x)	.04	0.07	.518	[-.09; .17]
	Hospitalizations (x)	**-.33**	**0.06**	**<.001*****	[-.43; -.21]
Hospitalizations (x + 43)					
	Motivation (x)	**-.34**	**0.05**	**<.001*****	[-.42; -.26]
	Infections (x)	.08	0.05	.12	[-.09; .17]
	Hospitalizations (x)	-.05	0.04	.226	[-.13; 04]

Figure 1. Lagged Pearson correlations between motivation and changes in both infections and hospitalizations with marked strongest correlation.

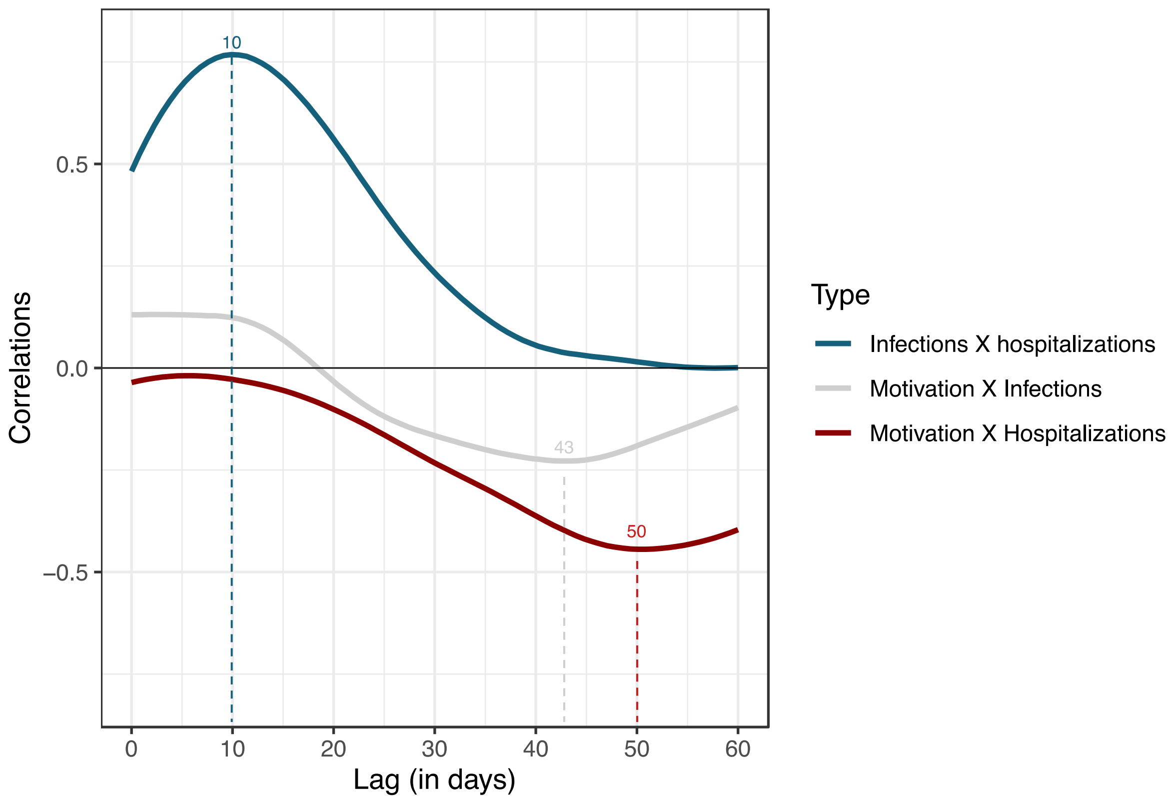
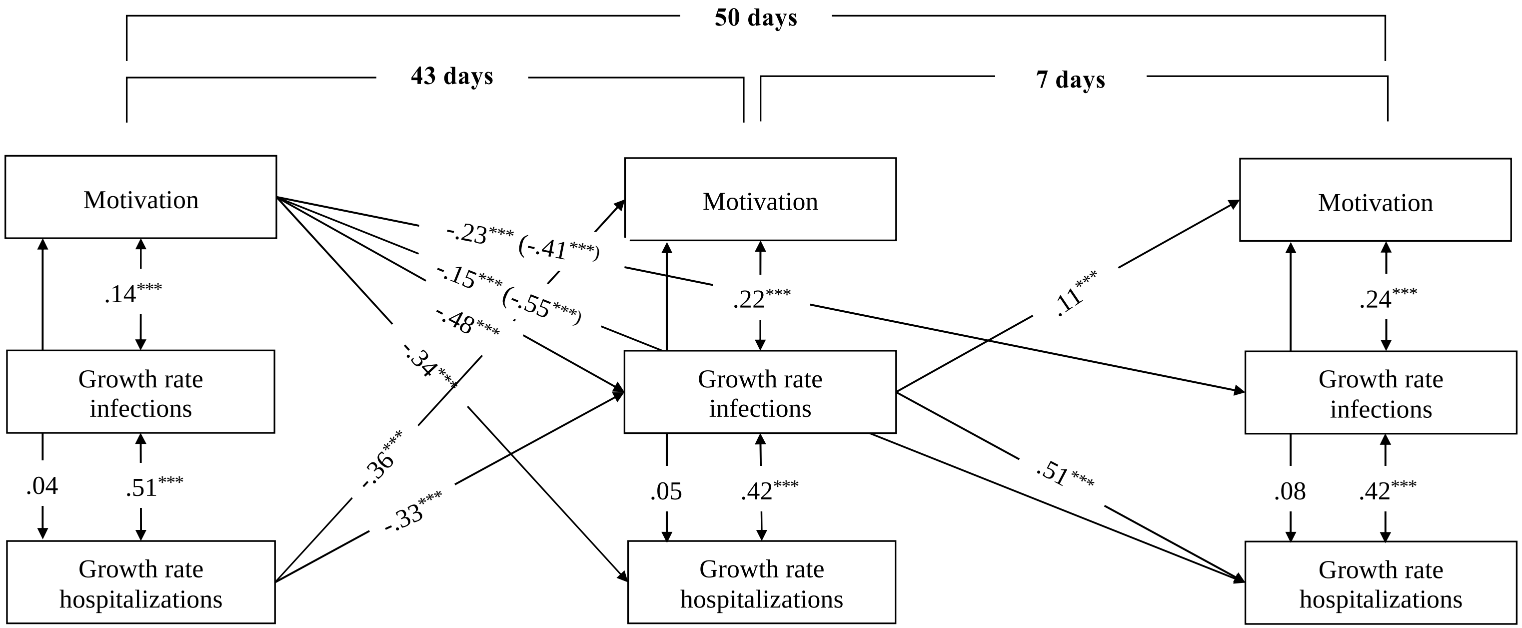


Figure 2. Significant cross-lagged pathways of a CL-SEM for motivation, infection and hospitalization growth rates across time.



$\chi^2(21) = 162.12$, $p < .001$; CFI = .94; TLI = .91; RMSEA = .06; SRMR = .02

Note. * $p < .05$, ** $p < .01$, *** $p < .001$