Why motivation for adhering to COVID-19 measures matters:

Investigating time-lagged associations with epidemiological indicators

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Abstract

To manage the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic, governments imposed public health measures requiring considerable effort and behavioral change from citizens. Grounded in self-determination theory, we investigate the relationship between citizens' motivation for adhering to health-protective behavior and epidemiological changes in SARS-CoV-2. Specifically, we investigated the concurrent (Hypothesis 1) and prospective (Hypothesis 2) association between daily motivation quality and daily actual growth rates in infections and hospitalizations in Belgium, thereby also testing the explanatory role of behavioral adherence to account for this prospective association (Hypothesis 3). Data were collected during the first 12 months of the SARS-CoV-2 pandemic using online surveys (N = 183,766; 7.2% missing days; 0% vaccinated; M_{age} = 50.41; 68.2% female) and the Google Mobility dataset. Multilevel models revealed that hospitalization rates (but not infection rates) are concurrently related to a better quality of motivation, with citizens identifying more with the value of measures and feeling less externally pressured to comply with them on a day with more hospitalizations. Across time, better quality of motivation predicted, respectively, lower infection and lower hospitalization rates 6 and 7 weeks later, with improved behavioral adherence, as assessed by self-reports and registered mobility, accounting for the benefits of motivation (i.e., mediation). We conclude that for a preventive policy to durably impact the epidemiological course, citizens need to fully identify with the importance of introduced health-protective measures such they volitionally adhere to them.

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

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The sudden emergence of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic in the beginning of 2020 challenged mankind in various ways. With millions of infections and a substantial number of deaths in various countries, the rapid virus circulation quickly became an international concern that needed the attention of policymakers. From March 2021 on, vaccines were distributed in the population, resulting in an effective reduction of SARS-CoV-2 infection, hospitalization, and mortality numbers (Eyre et al., 2022). However, before April 2021, that is, in the first year of the pandemic, no vaccines were available for the general population. As a result, to protect public health, stringent sanitary measures were required. Specifically, because the virus was transmitted person-to-person via respiratory droplets and aerosols (Borak, 2020), governments issued various, often intrusive, public health measures (e.g., keeping physical distance, wearing face masks, limit- ing social contacts, and washing hands).

Another challenge involved the ongoing assessment and predic- tion of infection and hospitalization numbers to monitor the epidemiological situation and to prevent a collapse of the national healthcare system. By making accurate assessments of the hypothe- sized evolution of the epidemiological situation, policymakers were in a better position to make timely decisions to prevent a new surge of infections. To this end, epidemiologists and biostatisticians relied on biomedical data to generate a number of time-lagged events. For instance, exposure to an infection and the onset of symptoms was estimated at a time lag of 2–14 days (Wei et al., 2022). As another example, national hospitalization rates followed the infection rates on average within 1–2 weeks (e.g., Faes et al., 2020). Yet, only little research up until today included a more fine-grained anal- ysis of the role of human behavior as a critical antecedent, not to mention its psychological and, in particular, its motivational determinants.

The Role of Human Behavior in the Epidemiology of the SARS-CoV-2 Pandemic

Over time, statisticians attempted to improve the prediction of SARS-CoV-2 evolution by including people's behavior as a preced- ing parameter of diagnosed infections. They did so based on simulated data (Gutiérrez-Jara et al., 2022), big data techniques (Lyu et al., 2023), and mobility data (Cot et al., 2021; Hu et al., 2021; Ilin et al., 2021; Mohammadi et al., 2022). To illustrate, mathematical models showed that compliance to self-isolation at home was negatively related to infection and hospitalization rates a few weeks later (e.g., Margraf et al., 2021; Talic et al., 2021), with individual-level interventions showing suppressed SARS-CoV-2 transmission (e.g., Doung-Ngern et al., 2020; Dwomoh et al., 2021). As another exam- ple, more mobility to people's workplaces, transit stations, or grocery stores, as detected by Google Mobility Reports, was shown to increase the infection rates 2 weeks later (García-Cremades et al., 2021).

Although these studies pointed to the critical role of human behavior in the evolution of the pandemic, research still faces several gaps. For instance, human behavior has been mainly captured in a more distal and indirect way (e.g., mobility), while the predictive validity of self-reported behavior has not been tested yet (Gollwitzer et al., 2022). Importantly, adherence to introduced measures largely depends on people's motivation to comply (e.g., Agusto et al., 2022), which is rarely assessed at all. The study of motivational pre- cursors of adherence may provide new insights into whether policy- makers can intervene earlier in the sequence. Therefore, we considered the possibility herein that motivation may serve as a critical early indicator in the causal chain that would predict the epidemiological course at an early stage.

The Role of Motivation in the Epidemiology of the SARS-CoV-2 Pandemic

Behaviors to counteract infection risk largely result from people's motivation to perform COVID-safe behaviors (Van den Broek- Altenburg & Atherly, 2021). Using the framework of

Self- Determination Theory (SDT; Ryan & Deci, 2017), the current research focuses on different types of motivation that have been shown to be relevant in predicting people's behavior. Specifically, SDT distinguishes between different types of extrinsic motivation that vary in their level of internalization and ownership (Vansteenkiste et al., 2023). In the case of identified motivation, adherence to the public health measures is perceived as necessary, useful, and congruent with one's personal values (e.g., solidarity and health). Because the reason for adhering to the measures is fully internalized, measures are volitionally adhered to. Partial internalization occurs when citizens adhere to measures for internally con- trolling reasons, such as the avoidance of guilt or the duty to act as a responsible citizen. In the case of introjected motivation, the reason for adhering to the measures resides inside the person but is buttressed with internal pressure. Finally, in the case of external motivation, cit- izens comply with the measures based on the expectations of others and the avoidance of critical remarks and sanctions. The reason for adherence is not internalized at all and external motivation represents the most pressured or controlled form of motivation.

These different types of extrinsic motivation yield differential predictive validity for various outcomes. For instance, several meta- analyses in education (Howard et al., 2021; Vasconcellos et al., 2020) and work (e.g., Van den Broeck et al., 2021) showed that identified motivation is associated with more adaptive outcomes, such as higher academic achievement, engagement, well-being, and persistence. In contrast, external motivation is related to more maladaptive outcomes, such as higher dropout intentions, lower self-esteem, and lower engagement. Introjected motivation is typically situated in between and comes both with some benefits and some costs.

In the healthcare domain, a substantial body of SDT research has focused on the internalization of health behaviors, like eating regulation (Verstuyf et al., 2012), dental care (e.g., Halvari et al., 2019), smoking (e.g., Williams et al., 2011), physical activity (Romero-Blanco et al., 2020), and medication compliance (Williams et al., 1998). The more people identified with the reasons for engaging in such behaviors, the more likely they were to persist and the less likely they were to relapse into their unhealthy routines. In contrast, those who felt pressured were more likely to give up, especially when facing obstacles (Gillison et al., 2019).

People who reported more identified motivation to adhere to social restrictions during the pandemic were more likely to avoid social con- tact during the Christmas holidays in 2020 (Guay et al., 2021), spent more time at home (Legate & Weinstein, 2022), and showed a greater intention to adhere to physical distance measures (Guay et al., 2021; Legate et al., 2022; Magrin et al., 2023). Further, across a series of three studies, Morbée et al. (2021) found positive associations between identified motivation and adherence to the measures, while those scoring high on external motivation reported less adherence. The effects of introjected motivation fell in between: it yielded a unique positive association with concurrent adherence but failed to predict adherence across time. Similar findings emerged when predict- ing people's vaccination intentions based on motivational differences. Identified motivation predicted positively concurrent vaccination intentions (Van Oost et al., 2022), a greater likelihood to subscribe to a vaccination waiting list and to effectively take up a vaccine (Schmitz et al., 2022), and the willingness to take a booster or annual vaccine 1 year later (Waterschoot, Van Oost, et al., 2023). External motivation yielded either a nonsignificant or a slight negative association with these critical vaccination behaviors.

Today, it is safe to conclude that citizens' type of motivation mattered for their health behavior during the pandemic. Although people felt pressured to comply with the measures at some point during the pandemic, what appears especially critical for adherence is that they identified with its value. Yet, what is unclear is whether the quality of motivation, as a fundamental antecedent of people's (self- reported) behavior, would also account for epidemiological changes during the pandemic. Furthermore, it remains unclear whether motivation, as a more distal variable, allows to predict the epidemiological course earlier than nonpsychological registered data such as mobility data (García-Cremades et al., 2021).

The Present Study

The present study attempts to bridge the gap between, on the one hand, the knowledge of individuals' type of motivation as a significant predictor of people's behavioral adherence to public health measures and, on the other hand, epidemiological parameters. Specifically, the aim of the present large-scale study was to examine the day-to-day associations between two types of motivation (i.e., identified and external) and changes in concurrent (i.e., on the same day) and prospective (i.e., time-lagged) growth rates of infections and hospitalizations.

In terms of concurrent associations between the growth rate in infections and hospitalizations and motivation, one possibility is that worsening epidemiology may have an overall motivating effect, thus leading to both enhanced external and enhanced identified motivation. Yet, in light of prior work showing that risk severity is a critical resource of internalized motivation for health-protective measures (Waterschoot et al., 2024), we reasoned that rising hospitalization numbers (and to a lesser extent rising infections) may especially predict more identified motivation. Presumably, on days with higher hospitalization growth rates, people develop a greater aware- ness of risks for themselves and vulnerable populations. Such enhanced risk perception then prompts a more volitional decision to take responsibility to contribute to the societal goal of limiting virus circulation. In light of this reasoning, we expected that a growth rate in hospitalizations on a given day would foster a greater endorsement (i.e., internalization) of COVID-19 restrictions on that day, thus contributing to higher identified and lower external motivation (Hypothesis 1).

This positive association at the concurrent level may change as time passes, and even become negative. Indeed, continuing the example: higher levels of identified motivation may result in lower virus trans- mission through increased adherence to behavioral measures, and, consequently, predict lower infections and lower hospitalizations later in time. Therefore, we examined prospective day-to-day associations in which we expected identified and external motivation at one point in time to be, respectively, negatively and positively related to infection and hospitalization rates several weeks later (Hypothesis 2).

The beneficial effect of identified motivation was expected to result from people's adherence to health-protective measures. We therefore include two different behavioral indicators to study its mediating or explanatory role, that is, daily self-reported adherence and daily regis- tered mobility by Google (Hypothesis 3). Figure 1 presents a figure of the conceptual model that was tested in the current study. We refrained from formulating an exact time lag but expected a time lag of several weeks rather than days. Indeed, 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 the time to symptom onset (2–14 days), the time to perform a test, the time to receive the result (0.5–1 week), and the timing of the registration of cases (e.g., Courtemanche et al., 2020; Faes et al., 2020; Lyu & Wehby, 2020; Pellis et al., 2021; Wei et al., 2022).

In testing these concurrent and prospective associations, we focused on the between-day variance in motivation, while statistically partially out the within-day or between-person variance. This is because epidemiological parameters varied from day to day while being constant across individuals within a given day. Further, to test for the robust role of daily motivation, we included a wide range of relevant pandemic-related covariates that were found to sig- nificantly modulate epidemiological changes. Specifically, we con- trolled for the stringency of measures, which affects COVID-19 transmission (e.g., Zhang et al., 2022) and people's adherence to health-protective measures (Waterschoot et al., 2023); the duration of the crisis, which may be associated with increasing corona fatigue and lower behavioral adherence to the measures (Petherick et al., 2021); the period of the year, as holiday periods typically go along with increased COVID-19 transmission due to a greater number of social gatherings and travels (Mehta et al., 2021); the day of the week, as fewer registrations were made during the weekends for sev- eral reasons (e.g., doctors and labs were closed); and, finally, we include two weather parameters (i.e., temperature and sunshine duration) as winter conditions (i.e. lower temperature, least sunshine) facilitating the spread of the virus, partly because people spend more time indoors (e.g., Majumder & Ray, 2021, McClymont & Hu, 2021).

Method

Participants and Procedure

In the context of a national research project in Belgium, called the Motivation Barometer (Vansteenkiste et al., 2023), we collected data through a serial cross-sectional research design. 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 SARS-CoV-2 pandemic in the Belgian population and obtained ethical approval from the Ethics Committee of

Ghent University. At both the beginning and the end of the questionnaire, contact information (e.g., information websites, email address) was provided in case of unclarities or in case the questionnaire had provoked negative thoughts and feelings.

For the current research, participants were those living in Belgium and who had participated in the study during the first 12 months of the pandemic, that is, from April 5, 2020 to April 19, 2021. The time window was limited because the vaccination campaign was rolled out at a fast pace after April 19, 2021, thereby impacting people's motivation and the epidemiological situation. In total, 237,767 independent participants started the online questionnaire, from which 24.73% was removed as they quitted the survey within 200 s, resulting in a final sample of 178,730 participants (M_{age} = 50.44; 68.1% female; 0% vaccinated participants) completing assessments on motivation and adherence to the mea- sures. Across the assessment period, spanning 379 days, there were 27 days with less than 10 participants having completed the questionnaire (7.12%), with a maximum gap of 3 days with miss- ing data 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. Daily levels of both the epidemiological situation (i.e., infection rates and hospitalization rates) and the average mobility of people (i.e., Google Mobility data set) were obtained from different sources (Google LLC, 2021; Sciensano, 2021).

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All procedures performed in studies involving human participants were accepted by the Ethical Committee of Ghent University. 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 partic- ipants included in the study.

We report how our sample size was determined, all data exclusions (if any), all manipulations, and all sanitary behaviors in the study, and we follow Journal Article Reporting Standards (JARS; Kazak, 2018). All data, analysis code, and research materials are available at https:// osf.io/5cdj7. Data were analyzed using R, Version 4.1.2 (R Core Team, 2021) and the packages imputeTS (Version 3.2; Moritz & Bartz-Beielstein, 2017), lme4 (Version 1.1-27.1; Bates et al., 2015), and mgcv (Version 1.8-38; Wood, 2011). The hypotheses were not preregistered because the current study and its research questions developed dynamically during the pandemic depending on changing circumstances.

Measures

Motivation to Adhere Public Health Measures

We assessed people's motivation to adhere to behavioral public health measures that were either legally required or strongly recommended by policymakers (Morbée et al., 2021) using adapted versions of the Behavioral Regulation in Sport Questionnaire (Lonsdale et al., 2008) and the Environmental Amotivation Scale (Pelletier et al., 1999). Following the stem "Over the past week, I've adhered to these sanitary behaviors because...", people answered four items assessing identified motivation (e.g., "I under- stand why these are important," "I can fully support this decision," "I find it personally relevant," and "They are an expression of my per- sonal values", $\alpha_{\text{between-days}} = .89$) and four items assessing external motivation (e.g., "I feel pressured to do this," "I feel compelled to do so," "Otherwise, I will be criticized," and "I want to avoid a sanc- tion," $\alpha_{\text{between-days}} = .81$). All items were to be rated on a 5-point scale ranging from 1 (totally disagree) to 5 (totally agree).

Behavioral Data

Adherence. We assessed people's self-reported adherence with one item for each of the three most important public health measures introduced in Belgium, that is, "to wash your hands fre- quently", "to avoid contact with the outside world as much as possible", and "to maintain physical distance from others." Participants were asked to indicate on a scale ranging from 1 (I do not adhere to it at all) to 5 (I totally adhere to it) the extent to which they followed each of the measures. Internal consistency proved acceptable ($\alpha_{\text{between-days}} = .84$).

Google Mobility Data. We assessed daily levels of people's mobility via the mobility measures at the country level from the COVID-19 Community Mobility Reports (Google LLC, 2021). The data are anonymized and aggregated based on Google users who have opted into their location history service. Mobility measure records the percentage change in total number of visitors to places classified as retail and recreation, grocery and pharmacy, parks, tran- sit stations, and workplaces compared to the median value of the same day of the week between January 3 and February 6, 2020. We calculated the average of these different locations to become one score for people's daily average mobility. The higher the score, the more people moved from one place to the other.

Growth Rates in COVID-19 Numbers

We obtained data on infections and hospitalizations from Sciensano, the National Public Health Institute of Belgium (Sciensano, 2021). The epidemiological situation is represented by calculating changes (per- cent) 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 num- ber 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 (dur- ing 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 complex calculations and interpretations.

Covariates

Stringency of Measures. Because the pandemic was character- ized by successive waves, the government imposed stricter sanitary behaviors (e.g., closure of schools, travel restrictions, strong limita- tions of social contact, etc.) during some periods and relaxed these sanitary behaviors during other periods. Hale et al. (2021) tracked the strictness of these rules and generated the Oxford COVID-19 Government Response Tracker (OxCGRT). OxCGRT provides a per- centage 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 pandemic. In general, studies have shown that the impact of governmental restrictions on the COVID-19 metrics emerged around the ninth day after their implementation (e.g., Pellis et al., 2021).

Weather, Holidays, and Weekends. Data from the Royal Meteorological Institute of Belgium was used to control for weather indicators across the pandemic. Specifically, daily temperature (in degrees Celsius) and sunshine duration (in minutes) were included. We included holiday periods and the distinction between week and weekend days as dichotomous variables.

Analysis Plan

Before conducting the preliminary and main analyses, we inspected the missing data, with missing values being as follows for the study variables: identified motivation (5.6%), external motivation (5.8%), and self-reported adherence (1.2%). Given the randomness of the missing data, Little's MCAR test: $\chi^2(4) = 713.31$, $p = .53$, we used the multiple imputation approach (i.e., 50 times in the current study) with the predictive mean matching algorithm, using all study variables as well as sociodemographic variables. This has the advantage of generating unbiased and accurate standard errors, which is appropriate for hypothesis testing (Schafer & Graham, 2002). Next, we imputed missing data on the levels of days using the linear interpolation algorithm, a method in which the missing value is estimated by linearly interpolating between the nearest nonmissing data points. All subsequent analyses and reported results rest on this (pooled) imputed data set. An overview of the descriptive evolution of study variables can be found in Figure 2A and 2B. We proceeded in five steps.

To quantify the synchrony between measures of motivation and the COVID-19 growth rates on a day-to-day level, we calculated in a first step the concurrent associations between the study variables by multilevel Pearson correlations. As the data were characterized by a multilevel structure, having dependent variance within days, we began by examining the intraclass correlation (ICC) representing the proportion of between-days variance (Musca et al., 2011). After extracting the variance situated at the between-persons level (i.e., within-days), we proceeded by inspecting the correlations at the between-day level.

In a second step, we analyzed how the association between motivation and epidemiological parameters would change when allowing an increasing time lag between both variables, thus shedding light on their prospective association. For the sake of exploration, we checked for a maximum time lag of 60 days through the cross- correlation function (CCF). The

CCF is a measure of similarity between two time series as a function of the displacement of one relative to the other, used to identify the time delay between two signals and to determine the size of the association between them. As CCF assumes time series variables to be stationary, we performed the Augmented Dickey–Fuller test showing evidence for stationarity when the p value is higher than .05. Stationarity indicates that the statistical properties of a time series do not change over time.

Once we determined the time lag with the strongest associations between motivation and epidemiological parameters, we continued with the Granger test in Step 3 to examine whether one time series is useful in forecasting another (Granger, 1969). However, it is important to note that the Granger test does not necessarily imply a cause-and-effect relationship. Instead, it is a way to examine whether past values of one variable contain information that helps predict future values of another variable, beyond the information contained in the past values of the second variable itself. Technically, the test contains the comparison between the fit of two regression models, one with only the lagged values of the predictor and another with both the lagged values of the predictor and those of the outcome.

The fourth step involves the testing of a more advanced and conservative multilevel model to shed light on the robustness of the time- lagged associations between day-to-day variance in motivation and day-to-day variance in outcomes (i.e., behavioral adherence, infection and hospitalization growth rates). Specifically, we checked for the contribution of time-lagged values of motivation in a more conservative way by controlling for several crisis-related variables that varied at the day-level (i.e., stringency of the measures, holiday periods, week-ends, daily temperature, average daily sunshine duration) and the lagged values of the outcome itself. Evidence for the latter is represented by the Autocorrelation Function, which is tested by the Durbin–Watson (DW) test. A DW value closer to 0 indicates a greater degree of positive autocorrelation (i.e., the variable is dependent on itself across time).

In a fifth and final step, we performed multilevel modeling, examining whether behavioral adherence, either self-reported or objectively registered, would mediate the association between quality of motivation and prospective infection and hospitalization growth rates. This is done by, first, testing to what extent the initial effect of motivation quality on the study variables remains after controlling for the crisis-related covariates. In the output, we present the standardized coefficients, the p value for the sake of statistical significance, the partial eta-squared for the sake of clinical significance, and the relative importance weight of model parameters. The latter should be interpreted as the proportion of total explained variance in the outcome variable by the model that is relatively explained by each model parameter. Second, we extended these models to a multilevel structural equation model to calculate indirect effects between motivation quality and the epidemiological parameters through the behavior variables as mediators (i.e., self-reported adherence, mobility; as presented in Figure 1). Furthermore, we tested a third model in which we loaded both self-reported adherence and mobility on a latent adherence factor. The goodness of fit of the models was evaluated by the root-mean-square error of approximation (RMSEA), the standardized-root-square residual (SRMR), and comparative fit index (CFI), where a combination of an RMSEA below .06, an SRMR value below .09, and a CFI of at least .90 suggests a good model fit (Kline, 2015). Given the size of the current data set, we achieved approximately 95% power in a multilevel structural equation model including an effect size of .80 (Richard et al., 2003) and a general correlation structure.

Results

Preliminary Analyses

Between-Day Correlations

Table 1 presents the descriptive statistics and between-day Pearson correlations between the study variables, controlled for the between- person variance (i.e., variance within days). ICC-values support the use of a multilevel structure as there is a sufficient portion of variance on the between-days level. First, daily levels of identified motivation were positively related to daily levels self-reported adherence and hospitalization rates, while being negatively related to daily mobility. Also, the longer the crisis evolved, the lower the daily levels of identified motivation and the higher the daily levels of external motivation. Given that identified and external motivation were strongly negatively related, we calculated a difference score (i.e., subtracting external motivation from identified motivation), a variable that was labeled "quality of motivation." As can be expected, mobility was negatively correlated with self-reported adherence, meaning that people were moving more on days when levels of self-reported adherence were lower. Also, on days when epidemiological growth rates were higher, mobility indices were lower. This was also the case for days later on in the crisis, those with a higher temperature and those with stricter measures.

Table 1 also shows the Durbin–Watson values close to zero, indicating a general tendency toward autocorrelation on a daily level (see Figure S1 in the online supplemental materials). Across time, auto- correlations of infection rates decreased the fastest. Specifically, after 15 days, the autocorrelations for infection rates are below .20, while this is only the case for hospitalization rates and quality of motiva- tion after 30 days. The finding of autocorrelations in the current set of variables is important, as we need to check for variables' own lagged values in the upcoming analyses.

Time-Lagged Correlations

All study variables met the criterion of stationarity across time (all ps . .05). For this reason, we could proceed with calculating the CCF (i.e., representing the time-lagged correlations) between the quality of motivation and adherence (self-reported, mobility) and epidemiological indicators (infection, hospitalization rates), which can be found in Figure 3. As can be noticed, the time lag of the peaking correlation between quality of motivation and outcomes varied by outcome. Specifically, quality of motivation related most strongly to self- reported adherence with a time lag of 0 day and mobility data with a time lag of 16 days. The strongest negative relations between quality of motivation and infection growth rates were observed 42 days later and with hospitalization growth rates 49 days later. Then, we per- formed four Granger tests to help us interpret the implications of these time-lagged correlations. The findings, reported in Table 2, all pointed to the same conclusion: quality of motivation was significantly related to prospective self-reported adherence, mobility, infection, and hospitalization rates while controlling for these outcomes at an earlier point in time. Yet, a reverse pattern from the outcomes to the quality of motivation over time was not detected.

Primary Analyses

Multivariate Modeling

Multilevel linear modeling was used to check for the robustness of the time-lagged correlation, thereby accounting for the between- persons variance. As can be noticed in Table 3, the positive association between motivation quality and self-reported adherence at day 0 remains significantly positive, even after controlling for the crisis- related covariates and the lagged values of self-reported adherence 1 week earlier. In addition, the negative association between quality of motivation and mobility 13 days later, infection rates 42 days later and hospitalization rates 49 days later remained significant after various covariates. Specifically, these models provide evidence for a large effect on the role of quality of motivation in the prediction of epidemiological parameters, with daily motivation accounting for 14% and 16% of the variance in, respectively, infection and hospitalization growth rates. In terms of covariates, especially sunshine duration and the stringency of the measures had unique main effects, indicating that on days with fewer hours of sunshine and a less stringent set of measures, people were moving more (higher mobility rates) and the growth rate of infections and hospitalizations was higher.

Mediational Analyses

The models in Table 3 were extended to a multilevel-mediation model to examine the proposed model in Figure 1. Specifically, a sequence of variables was built with adherence serving as an explanatory mechanism between quality of motivation and infection rates, with infection rates being linked to hospitalization rates later in time. Three mediation models were tested, with self-reported adherence (Model 1), mobility (Model 2), and a combined, latent score (Model 3) serving as explanatory mechanisms. The output of these models is visualized in Figure 3. All three models yielded a satisfactory fit and the indirect effects from the quality of motivation to infection and hospitalization rates through behavior measurements were significant in all of the models. Yet, an additional direct effect from the quality of motivation to infection rates remained significant, suggesting that adherence plays a partial (instead of a full) mediating role.

Discussion

During the first year of the SARS-CoV-2 pandemic, most governments imposed a variety of behavioral public health measures (e.g., restricting physical contact) to prevent the spreading of the virus. Past work has shown that people's type of motivation, as reflected by the voluntary endorsement of the necessity and value of such measures, serves as a reliable predictor of people's adherence to imposed behavioral restrictions (Legate et al., 2022; Morbée et al., 2021). Yet, what remains unclear is whether people's type of motivation may also help to understand the evolution in the epidemiology of the pandemic itself, with the effects of motivation impacting critical objective health outcomes. Specifically, we were interested in how daily variation in people's motivation would prospectively relate to fluctuations in the epidemiology. We formulated the general hypothesis that citizens' quality of motivation, as reflected by identified and external motivation, would predict their future health behavior to eventually reduce virus circulation, as indexed by lower infection and hospitalization rates.

Key Findings

Using a large data set collected across the entire first year of the pan- demic, a sufficient amount of variance in motivation was found to be present at the day level (i.e., on some days the population was more volitionally motivated whereas on other days they felt more pressured to adhere to the measures). This allowed us to calculate associations between motivation and outcomes at a population level. Here, four key findings deserve to be mentioned.

First, congruent with prior studies (Waterschoot et al., 2023), within the same day, hospitalization rates were associated with higher identified motivation, lower external motivation, and higher (self-reported) adherence on the same day. However, no direct asso- ciation for infection rates was significant. The reason why days with higher hospitalization rates foster a greater willingness to adhere to the measures is that people perceive higher risks on such days (Waterschoot et al., 2024). Indeed, risk perception and, in particular, the perception of becoming severely ill serves as a critical factor fostering greater internalization of even stringent measures.

Further, previous studies across the globe, including Canada (Guay et al., 2021), Belgium (Morbée et al., 2021), the United States, and the United Kingdom (Legate & Weinstein, 2022) have shown that interpersonal variation in identified motivation predicts interpersonal variation in behavior. In some cases, people even spontaneously adapted their social behavior and reported more face mask use when they noticed that the situation was deteriorating and even before governments imposed behavioral sanitary measures (e.g., Guan & So, 2020). The current study goes beyond this work by showing that these motivation-adherence dynamics even apply to a day-to-day level. A second important finding thus concerns days that the population was more willingly motivated, they also indicated being more adherent to the introduced measures. This association was observed both for self-reported adherence as well as objective markers of mobility. Interestingly, at that level, external and identified motivations were highly incompatible. That is, on a day that citizens could identify with the value of health-protective measures, they did not feel externally pressured to comply with them. In con- trast, when such perceived value was missing, people reported feel- ing pressured, presumably because measures were perceived as illegitimately severe on such days (Waterschoot et al., 2023).

Third, the most innovative finding concerns the observation that quality of motivation is negatively related to changes in infection and hospitalization rates, respectively, 6 and 7 weeks later. This association was fairly strong in terms of effect sizes 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). Associations for these covariates were in line with expectations, especially with colder and darker days being related to more infection and hospitalization rates. In line with the concept of "pandemic fatigue" (i.e., people becoming tired and indifferent toward the pandemic;

Petherick et al., 2021), pandemic duration was related to more external motivation and lower identified motivation. Further, during holiday periods, people reported lower quality of motivation, while they reported higher quality of motivation on days when more stringent measures were put in place. Presumably, during holiday periods, people are more inclined to gather with others and, hence, sticking to the measures (e.g., keeping social distance; minimizing social contact) is more challenging and feels more like a daunting duty. More stringent measures highlight greater circulating risks, such that the measures are perceived as more necessary and get more easily internalized and accepted (Waterschoot et al., 2023).

The difference in time lag for infection rates (6 weeks) and hospitalization rates (7 weeks) dovetails nicely with earlier literature showing infections impacting hospitalizations after 7–13 days (e.g., Faes et al., 2020). Different mechanisms may account for the observed time lags, such as the incubation period of 4–6 days, the time interval between the first appearance of symptoms and the visit to a doctor, the actual testing, and the official registration (e.g., Wei et al., 2022). Also consider the time delay in acquiring test results, allowing people to inadvertently infect each other (Sah et al., 2021). 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 SARS-CoV-2 outbreak during the period of the current study (Coletti et al., 2021; Pellis et al., 2021).

Fourth, in a multilevel process model, we tested the entire sequence from motivation to hospitalization rates 7 weeks later. Indirect effects confirmed the proposed integrative model in Figure 1: quality of motivation predicted people's behavioral adherence, which then predicted infection rates more than a month later. In turn, infection rates predicted hospitalization rates 1 week later (see Figure 4). Interestingly, daily quality of motivation still yielded a direct contribution in the pre- diction of daily infection rates above and beyond the role of adherence. One possibility is that our measure of behavioral adherence was not inclusive enough; for instance, wearing mouth masks was not assessed as this was only required from the summer of 2020. It should be noted that our behavioral measure concerns people's adherence on a single day, assessed retrospectively to the previous week; possibly, if a composite score of adherence was created across several days, the explanatory role of adherence may be enhanced and the direct role of quality of motivation diminished.

Overall then, our data show how behavior and epidemiology form a complex, dynamic system regulated by a negative feedback loop, with the epidemiological situation being related to people's motivation (and behavior), which in turn was associated with the epidemiological situation after a delay. From a practical point of view, policymakers 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 (Legate et al., 2022; Martela et al., 2021; Teixeira et al., 2020). For instance, this could be done by communicating more clearly (e.g., using visuals) about different prospective scenarios to show the consequences of people's behavior (i.e., "if-then" scenarios; Petersen et al., 2022).

Limitations, Constraint on Generality, 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 Belgium because participation was based on the respondent's decision. This self-selection can be driven by situational, psychological, or sociodemographic elements. For example, respondents might have a computer, tablet or smartphone and inter- net 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. Self-selection was corrected to some extent through statistical methods (e.g., adding weights to the data set). 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 (Lavallée & Beaumont, 2015).

Second, the downside of the current serial cross-sectional design, which focuses on the day-to-day level of motivational dynamics, is that the predictive role of motivation across time could not be examined. Although prior studies revealed that between-person differences in motivation are predictive of their concurrent (Moore et al., 2022) and prospective (Morbée et al., 2021) adherence to COVID-19 restrictions, it remains to be shown whether motivational differences also predict the probability of getting a positive COVID-19 diagnosis later in time (e.g., Andrasfay et al., 2022). Thus, including objective markers, such as people's diagnosis of a COVID-19 infection, as an outcome of interpersonal differences in motivation would be an important contribution to the field.

Third, 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 in the construction of predictive models regarding the SARS-CoV-2 pandemic (e.g., Faes et al., 2020). Earlier efforts showed that such models, which are mainly based on the registered COVID-19 numbers itself, provide predictions between 5 and 40 days (e.g., Hussein et al., 2022). 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.

Fourth, other covariates might be taken into account in the association of motivation with the COVID-19 numbers. For instance, we currently only incorporated data from the first year of the pandemic, whereas the pandemic lasted for another 1.5 years. In this period, a growing proportion of the population became vaccinated, variants of the coronavirus changed in nature and the population might have experienced a high level of pandemic fatigue. Therefore, some of the observed dynamics herein may not generalize to this period and other covariates may have a more significant impact. Also, next to some sociodemographics, we did not account for other between- person predictors that could be associated with motivation and behavioral adherence, such as differences in cognitive beliefs (e.g., Jang et al., 2021) or personality (e.g., Moore et al., 2022).

Conclusions

The current findings showed a remarkable "dance" between people's quality of motivation for behavioral measures and critical SARS-CoV-2 epidemiological parameters. Increases in epidemiological parameters on a given day relate to higher levels of people's quality of motivation to adhere the sanitary behaviors on that day. This higher level of motivation quality results in a better epidemiological situation later in time which, in turn, induces a decline in quality of motivation for behavioral measures and, thus, more virus spreading and increasing SARS-CoV-2 infections. Policymakers may greatly benefit from close monitoring of motivational changes because this would allow them to anticipate epidemiological changes way ahead. In addition, inducing the quality of motivation for behavioral measures through appropriate communication strategies would allow policymakers to lead the dance and eventually reduce the number of infections and hospitalizations.

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Table 1

Between-Day Correlations Between the Study Variables

Variables	*M*	*SD*	ICC	DW values	1	2	3	4	5	6	7	8	9	10
Motivation														
1. Identified motivation	3.66	1.10	.10	0.21	—									
2. External motivation	2.58	1.05	.06	0.25	−.86***	—								
3. Quality of motivation	1.04	0.76	.09	0.18	.97***	−.96***	—							
Adherence														
4. Self-reported adherence	4.18	0.83	.07	0.49	.66***	−.46***	.73***	—						
5. Mobility	−23.90	12.79	—	0.62	−.24***	.09*	−.17**	−.30***	—					
Epidemiological parameters														
6. Cases growth rate	1.86	30.94	—	0.04	.03	−.03	−.03	−.09	−.55***	—				
7. Hospitalization growth rate	3.55	32.75	—	0.06	.13**	−.09**	.11**	.11*	−.41***	.72***	—			
Covariates														
8. Crisis duration	183.5	105.80	—	0.01	−.38***	.48***	−.44***	−.47***	.17**	.09	.20***	—		
9. Daily temperature	11.37	6.60	—	0.12	−.07	−.09	.00	.05	.22***	.19***	.12*	−.66***	—	
10. Daily sunshine minutes	292.43	275.36	—	0.71	−.05	−.08	.00	−.02	.01	−.02	−.04	−.40***	.46***	—
11. Stringency index	61.93	9.07	—	0.03	−.04	.09	-.07	.01	−.66***	−.64***	−.52***	−.11*	−.15**	.26***

Note. Depending on the level of assessment, some variables have no ICC value. ICC = intraclass correlation; DW = Durbin–Watson. All DW values were significant on the $p < .001$.
$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

Table 2

Output of Granger Tests Between Motivation Quality and Study Variables

		$X \rightarrow Y$		$X \leftarrow Y$	
Variable X	Variable Y	F	p	F	p
Quality of motivation	Adherence	4.73	.001**	0.05	.95
	Mobility	4.61	.02*	3.29	.07
	Infection rates	2.14	.01*	0.14	.71
	Hospitalization rates	11.58	<.001***	0.03	.86

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

Table 3

Output of Multilevel Models for Quality of Motivation in Prediction of Study Variables

Predictors	Outcomes			
	Self-reported adherence	Mobility	Infection rates	Hospitalization rates
Outcome (lag 1 week)	.23*** (.13) (.06)	−.41*** (.52) (.20)	.45*** (.48) (.32)	.53*** (.39) (.36)
Crisis-related covariates				
Daily temperature	.08* (.02) (.06)	.11** (.05) (.12)	−.01 (.00) (.01)	.03 (.02) (.02)
Sunshine duration	−.10** (.02) (.20)	.13*** (.01) (.13)	−.11** (.06) (.09)	−.14*** (.09) (.11)
Stringency index	.06 (.01) (.07)	−.36*** (.14) (.17)	−.41*** (.24) (.36)	−.27*** (.14) (.24)
Weeks (weekends)	.00 (.00) (.12)	.15*** (.05) (.25)	.01 (.00) (.02)	.01 (.00) (.01)
Holidays (yes)	.04 (.00) (.05)	−.11*** (.03) (.09)	04 (.00) (.06)	−.07 (.01) (.10)
Quality of motivation	.70*** (.36) (.44)	−.14*** (.10) (.30)	−.21*** (.33) (.14)	−.23*** (.39) (.16)
Time lag	0 days	13 days	42 days	49 days
Model information				
R^2	.71	.60	.64	.61
Maximum VIF	1.54	1.80	1.82	2.17

Note. Numbers between brackets refer to partial eta-squared and relative importance weights, respectively. VIF = variance inflation factor.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Figure 1

Conceptual Model

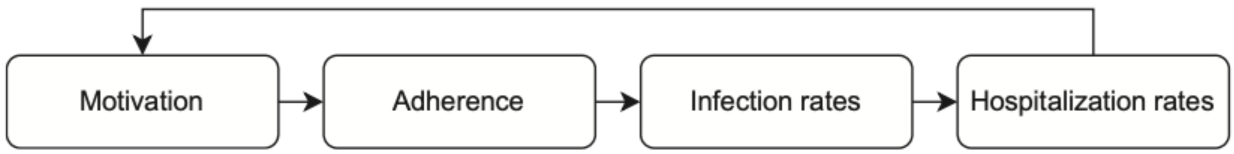
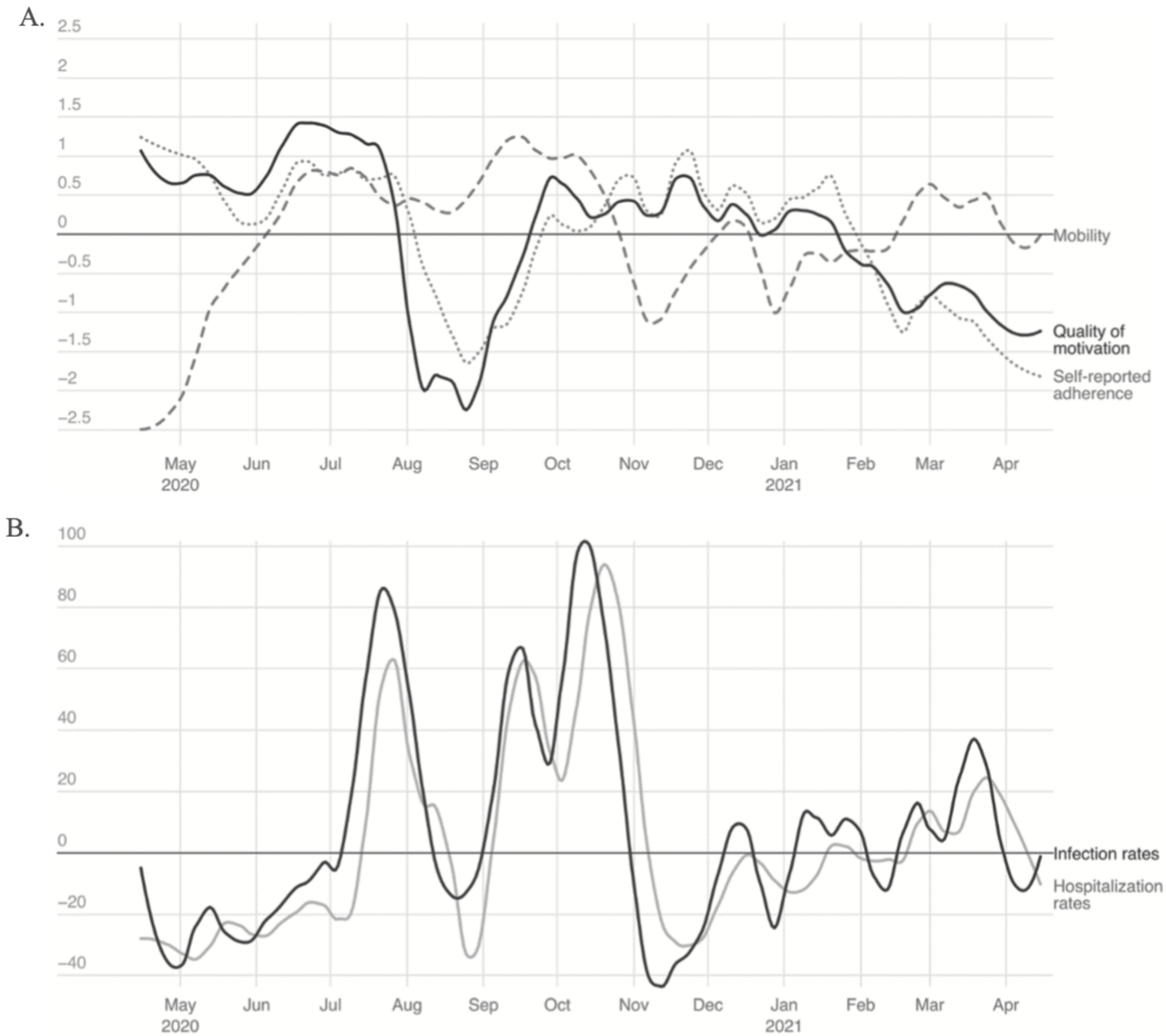


Figure 2

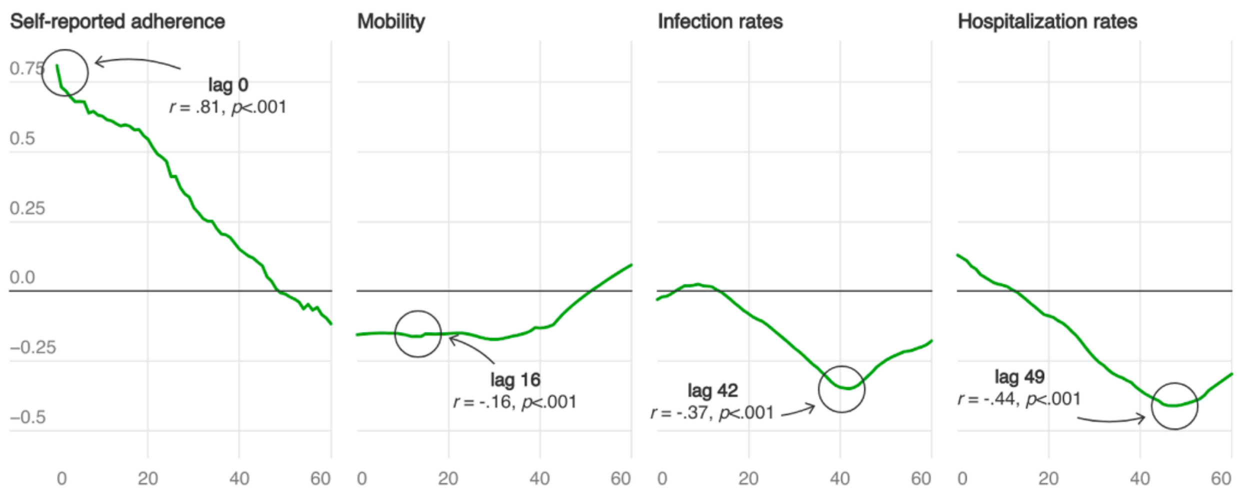
Descriptive Evolutions in Study Variables Across Time



Note. Panel A describes the quality of motivation and behavioral data. Panel B presents the epidemiological parameters across time. For the sake of clarity and comparability, variables in Panel A were standardized due to different scales.

Figure 3

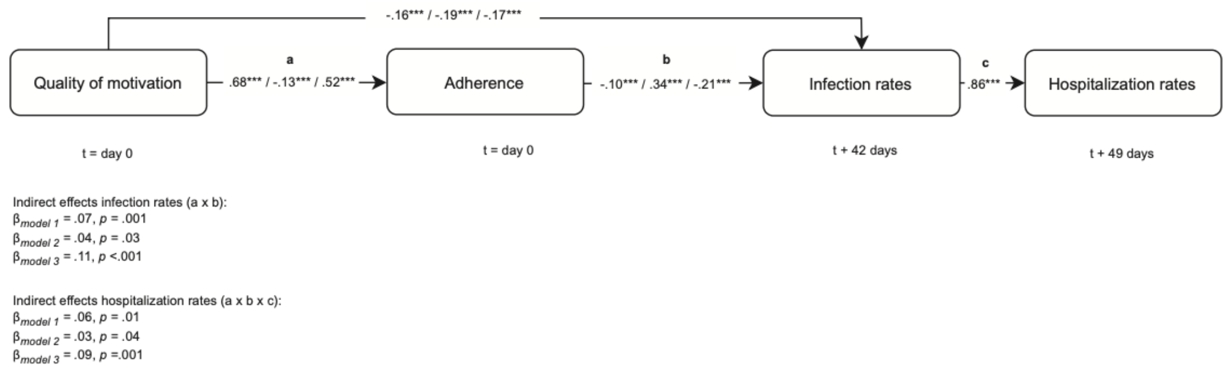
Time-Lagged Correlations Between Quality of Motivation and Outcomes



Note. See the online article for the color version of this figure.

Figure 4

Visualization of Multilevel Structural Equation Models



Note. Coefficients refer to the output of the three separate models with mediator for self-reported adherence (Model 1), mobility (Model 2), and latent adherence (Model 3); t = time.
*** $p < .001$.