Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Stuck in the past or living in the present? Temporal focus and the spread of COVID-19

Stuart J. Barnes
CODA Research Centre, King’s Business School, King’s College London, Bush House, 30 Aldwych, London, WC2B 4BG, United Kingdom

ARTICLE INFO
Keywords:
ARIMA model
COVID-19
Pandemic
Temporal focus
Dynamic regression
Text analytics

ABSTRACT
Research has shown that the temporal focus of individuals can have a real effect on behavior. In the context of the COVID-19 pandemic, this study posits that temporal focus will affect adherence behavior regarding health control measures, such as social distancing, hand washing and mask wearing, which will be manifested through the degree of spread of COVID-19. It is suggested that social media can provide an indicator of the general temporal focus of the population at a particular time. In this study, we examine the temporal focus of Twitter text data and the number of COVID-19 cases in the US over a 317-day period from the inception of the pandemic, using text analytics to classify the temporal content of 0.76 million tweets. The data is then analyzed using dynamic regression via advanced ARIMA modelling, differencing the data, removing weekly seasonality and creating a stationary time series. The result of the dynamic regression finds that past orientation does indeed have an effect on the growth of COVID-19 cases in the US. However, a present focus tends to reduce the spread of COVID cases. Future focus had no effect in the model. Overall, the research suggests that detecting and managing temporal focus could be an important tool in managing public health during a pandemic.

1. Introduction

The World Health Organization declared COVID-19 a global pandemic on the March 11, 2020. As of the February 5, 2021, globally, there were 105 million cases and 2.3 million deaths from the disease (CRC, 2021). In the US, there were 26.4 million cases and 449,020 cases until the February 4, 2021 (CDC, 2021). The death toll of US citizens from COVID-19 now exceeds that of World War II (405,000; Sergeant and Padilla, 2021). A challenge in all countries has been the effective implementation of rules, regulations and guidance to prevent the spread of COVID-19.

Notwithstanding the health risks and the rising number of confirmed cases of COVID-19, controlling the spread of the disease in the US has been extremely challenging. Clearly there is a strong divergence in views regarding attitudes and behavior towards health controls in the United States. This study posits that part of the explanation for these differences in perspective is the temporal focus held by citizens at a particular point in time. The concept of temporal focus is defined as “the extent to which individuals characteristically direct their attention to the past, present, and or future (Shipp and Aeon, 2019, p. 37). For example, those citizens with a past focus may be more likely to resist new rules and restrictions, while those with a present focus may be more likely to follow them (Sobol-Kwapinska et al., 2020).

This study attempts to understand some of the underlying behavioral drivers for the spread of COVID-19 cases. The research involved the collection of a big data set of tweets with COVID-19-related terms over more than 10 months during the pandemic. The data was then analyzed using dynamic regression via autoregressive integrated moving average (ARIMA) analysis. The research question for this study is: Does temporal focus influence behaviors that lead to changes in the number of COVID-19 cases?

This manuscript makes two key contributions. First, it provides an original contribution via the novel research process developed that combines text analytics and advanced time series analysis from user-generated content with other sources to test theory and hypotheses. This is a highly unique research method and answers a recent call for big data analytics methods to further investigate temporal focus (Shipp and Aeon, 2019). The second contribution of the paper is theoretical. This study tests the application of Temporal-Focus Hypothesis (TFH) in explaining human behaviors that have an effect on the spread of the COVID-19 virus. People differ in their focus on the past, present and future and this may help to explain different behaviors regarding public health measures. The findings from the study have practical value, suggesting that detecting and managing temporal focus could be an
important tool in managing public health during a pandemic.

The structure of the paper is as follows. In the next section, the conceptual and theoretical foundation for the study is presented, including hypotheses. The third section provides details on the method and steps in the research process. Section four provides the results of dynamic regression analysis and the testing of the hypotheses. The final section discusses the findings and provides implications for research, policy implications, and limitations.

2. Theory and hypotheses

In this section, the underlying conceptual and theoretical foundation for the research is explained, including the temporal focus hypothesis and related research findings, and the contribution of big data analytics. The hypotheses are then presented.

2.1. Temporal focus theory

People differ in their perceptions of the past, present and the future (Bluedorn, 2002; Rappaport, 1990). Some individuals may dwell on the past, while others live in the present or have visions for the future. The concept of temporal focus is defined as “the extent to which individuals characteristically direct their attention to the past, present, and or future” (Shipp and Aeon, 2019, p. 37). Indeed, early work by Lewin proposed the importance of an overarching time perspective in understanding individual behavior (Cartwright, 1951).

The development of an individual’s time perspective is complex and includes a mix of “macro” and “micro” forces. This includes the effects of socialization in early childhood from significant others in the milieu and the impact of national culture and language (Shipp and Aeon, 2019). For example, the work of Hofstede has found significantly different temporal focus between citizens in the US and China (Hofstede et al., 2010). China has a much stronger past temporal focus prioritizing its long history, traditions, and respect for ancestors than North America, which has a much shorter national history (Guo et al., 2009; Shipp and Aeon, 2019). Nevertheless, temporal focus can also change within individuals over time: for example, those in adulthood tend to focus less on the present and more on the past or the future, whilst older people tend to focus less on the future and more on the past (Laureiro-Martinez et al., 2017). Moreover, temporal focus can even vary significantly on a day-to-day basis, based on the level of attention to the past, present or future at a particular time. Rush and Grouzet (2012) found that temporal focus varied by between 63% and 69% on a daily basis.

Although earlier research on temporal focus tended to classify individuals based on past, present and future focus, this is an artificial boundary that prohibits a balance view of the changing nature of temporal focus (Shipp et al., 2009). Individuals have control over their attention and direct it according to role demands and external stimuli, including their focus on the past, present and future. Notwithstanding, cumulatively, individuals do tend to develop a general tendency to focus on particular time periods with different intensities (Zimbardo and Boyd, 1999). Front-back mapping refers to charting time onto spatial frames and is related to the amount of attention dedicated to the past and the future. The Temporal-Focus Hypothesis holds that the way that temporal concepts map within front-back mental space-time is a function of a person’s temporal focus – based on the level of attention devoted to the past, present and future – which varies according to such factors as an individual’s age, culture, and shifts in attention over time (de la Fuente et al., 2014; Bylund et al., 2020). Research has shown that moment-to-moment changes in temporal focus have corresponding changes in front-back mappings (de la Fuente et al., 2014; Li, 2018). Research by de la Fuente (2014) found that thinking about the future tends to map it into a frontal position, whilst giving attention to the past results in the reverse pattern of mapping.

Research has shown that different types of temporal focus tend to have different behavioral and attitudinal outcomes. There is a considerable body of research that suggests that a past temporal focus tends to be associated with negative outcomes: reviewing previous literature on past temporal focus, Shipp and Aeon (2019) conclude that “higher past focus may be maladaptive, causing various types of emotional stress” (pp.38–9). Past-focused individuals are more likely to be dissatisfied with their current employment (Shipp et al., 2009). Those with a past focus are also more likely to exhibit Internet addiction, as illustrated by Przepiorka and Blachnio’s (2016) survey of Facebook users. More generally, past-focused individuals tend to have lower satisfaction with life and to experience lower well-being (Drake et al., 2008; Rush and Grouzet, 2012; Stolarski and Matthews, 2016). Zhang and Howell (2011) found that while people with high neuroticism and a past negative time perspective were less satisfied with their lives – which is in concert with the findings of Zimbardo and Boyd (1999) – they found the opposite for those with high extraversion and a past positive and present hedonism time perspective.

Research into the impact of present temporal focus on attitudes and behavior is mixed. Stolarski et al. (2014) found that present-focused individuals tend to be more aggressive. Keough et al. (1999) found that present focus is associated with risk-taking, such as substance abuse, while Rothspan and Read (1996) found a correlation with unsafe sexual activity. Notwithstanding, Rush and Grouzet (2012) argue that a present focus and the ability to live in the moment is crucial for well-being, citing a considerable amount of research demonstrating that a present focus is related to greater general wellbeing (Shipp et al., 2009; Zimbardo and Boyd, 1999). Sobol-Kwapinska and Jankowski (2016) found that attentiveness to the present plays an important role in developing a balanced time perspective, creating a general positive attitude towards time.

A future temporal focus tends to be more abstract; according to construal level theory, a future focus is associated with fewer details than other temporal dimensions (Trope and Liberman, 2003). Zaleski et al. (2017) examined future anxiety and found a relationship with the future negative time perspective. Notwithstanding, future-focused individuals tend to be more focused on positive attitudes and behaviors. For example, Milfont et al. (2012) found that individuals with a future time perspective tend to exhibit higher pro-environmental behaviors, while Bruderer Enzler (2014) identified consideration of future consequences as a significant predictor of pro-environmental behavior. Similarly, Baumsteiger (2017) conducted three experiments and found that future-oriented individuals were more likely to behave pro-socially. Moreover, related to the context of this study, future-oriented individual also tend to care more about health status and health behaviors, as demonstrated in the panel study of Kehana et al. (2006) and the online survey research of Griva et al. (2014).

2.2. Measuring temporal focus: the contribution of big data analytics

Temporal focus is typically measured using self-reported scales, such as the Zimbardo Time Perspective Inventory (Zimbardo and Boyd, 1999). Shipp and Aeon (2019) note that big data and advanced analytics provides a new and unobtrusive way to study temporal focus by coding text. Traditional survey scale measures tend to be limited in terms of providing smaller samples of empirical evidence using at most hundreds or thousands of self-reported questionnaires; in obverse, online user-generated content can potentially provide insight into people’s attitudes, feelings and behaviors at a much larger scale with data from tens or hundreds of thousands of data points. Text analytics using big data sets can help ameliorate various aspects of bias that may be prevalent in surveys (Barnes et al., 2020), including social desirability bias (De Vaus, 1996), common method bias (Podsakoff et al., 2005), sampling error (Dillman et al., 2014; Singleton and Strais, 2009), recall bias (De Vaus, 1996), inattention bias (Brosnan et al., 2019), and measurement error (Dillman et al., 2014).

Park et al. (2017) develop and test a method for measuring temporal orientation via social media messages on Twitter and Facebook. They
future-oriented words and phrases such as a significant negative correlation between the prevalence of words on Twitter in the context of the spread of the human immunodeficiency virus (HIV). They find that a future focus identified in the text was correlated with a lower HIV prevalence. Ireland et al. (2015, p.270) conclude that: “Integrating big data approaches to text analysis and epidemiology with psychological theory may provide an expensive, real-time method of anticipating outbreaks of HIV and etiologically similar diseases.”

3. Method and research process

In this section the various steps in the research process are delineated. The study used dictionaries to analyze Twitter data from the US and official US data on the number of COVID-19 cases, combined with dynamic regression via ARIMA modelling in R. The steps in the research process are outlined in Fig. 1. In the next section, we examine the benefits of using ARIMA analysis. Subsequently, the paper examines the steps in the research process in more detail.

3.1. Dynamic regression using ARIMA analysis

ARIMA is able to capture very complex relationships in the data through its combination of techniques (Box et al., 2015). The autoregressive (AR) aspect refers to the removal of seasonality from time series to make it stationary (discussed further below). Finally, the moving average (MA) element refers the use of error terms from previous time points in predicting current and future observations. This process removes random movements from a time series. Residual seasonal components in the time series may also be taken into consideration in order to improve the accuracy of the model (seasonal AR and seasonal MA components – see section 3.3). ARIMA analysis may also include exogenous variables in order to improve the accuracy of models, and the relationship between independent and dependent variables may also be examined through “dynamic regression” using ARIMA errors (Hyndman and Athanasopoulos, 2018 – see section 3.4).

ARIMA differs from other longitudinal analysis techniques in the social sciences such as latent growth modelling (LGM) and multi-level modelling (MLM) in a number of ways. First, it focuses on a single-unit dependent variable over time. It is suitable in situations where there is suitable aggregate data for a phenomenon, but where individual data may be sparse or incomplete (as is the case in this study). Second, while LGM and MLM tend to be applied on data sets with only a few time periods, ARIMA is most suitable for time series with more than 50 time points (Yanovitzky and VanLear, 2007). Third, neither LGM or MLM adequately reflect the temporal character of a data set and do not capture trends that are caused by the internal dynamics of the variable under study (Hollander and Vliegenthart, 2008). This limitation is typically addressed via research designs with a small number of distinct time data points (often two, three or four) or with panel data sets (Shin, 2017). Notwithstanding, a key problem in such designs is that variables
are expected to vary at random, so the common practice of selecting data every three or four time units (Wilson et al., 2006), can easily result in the incorrect identification of a trend (Kelly and McGrath, 1988). ARIMA is designed to account for the complex internal dynamics of time series variables through the different mechanisms it employs, as explained above.

ARIMA focuses on determining underlying relationships for variables in the data set. Therefore, it is important that observations are not dependent on the time at which they are taken. If there are seasonal effects or trends that depend on the time index, any analysis of relationships will be heavily biased and inaccurate. Thus, ARIMA requires wide-sense stationarity, whereby the mean and variance or autocovariance are constant over time, implying that variance is not a function of time (homoscedasticity) and there is no pattern in covariance over time. Typically, a time series has systematic short-term fluctuations rather than random variations around a trend; such systematic patterns in the time series variables must be removed in order to accurately test the relationship between them, since correlations may simply be a product of the patterns (Shin, 2017). Thus, where necessary, time series data is transformed to make it stationary. This fulfills the criteria of the Wold theorem and enables modelling in the absence of systematic time bias.

3.2. Data collection, dictionary analysis, data preparation and exploration

This paper concentrated on Twitter user data from the US during the pandemic. Tweets related to COVID-19 posted during the period from the January 20, 2020 to the January 10, 2021 were downloaded. Tweets were identified using the tweet IDs collected by Banda et al. (2021). The entire corpus of tweet IDs was downloaded and then filtered for US tweets identified as being written in English (note: both are variables in the downloaded corpus). This study focused on the original tweets and did not consider retweets, to avoid double-counting. A total of 762,627 anonymized tweets were captured during this process (other tweets during this period were either not coded as “US” or “English” or no longer unavailable for download). Data on daily diagnosed COVID-19 cases was downloaded from the website of the Centers for Disease Control and Prevention (CDC, 2021). The early period that contained predominantly zero case data was excluded, up to and including the February 28, 2020, which was the last day in the data window reporting a zero daily case rate. The time series of US COVID-19 cases is illustrated in Fig. 2. This appears to show weekly seasonality (i.e. a sawtooth pattern) and a number of interim peaks, including after Easter, Independence Day, Thanksgiving and Christmas.

For past, present and future temporal focus the relevant dictionaries from LIWC2015 (Pennebaker et al., 2015a, 2015b, 2015b) were used. LIWC2015 contains approximately 6400 words across numerous categories. It includes 862 words related to time orientation, including 341 for past focus (e.g. ago, did, and talked), 424 for present focus (e.g. today, is, and now), and 97 for future focus (e.g. may, will, and soon) (Pennebaker et al., 2005b).

The analysis produced scores for each tweet, related to each word dictionary (“Past”, “Present” and “Future” temporal focus). Using the raw scores and word counts for each tweet, the number of words relating to each dictionary were then calculated for each tweet. Thus, each tweet may contain words with past, present and/or future focus. Overall, there were 217,767 tweets with at least one past-focused word, 508,062 with at least one present-focused word, and 136,946 with at least one future-focused word. Subsequently, construct count and COVID-19 case data were then aggregated into a daily time series format suitable for ARIMA analysis. This process involved calculating the percentage of total words with each type of temporal focus on each day in the time window. Descriptive statistics on the data set are given in Table 1. This shows that a present temporal focus was the most common (mean of 6.93%), followed by a past focus (mean of 1.86%). A future focus was much less common (mean of 0.90%).

The time series for the temporal focus variables used in the dynamic regression analysis are illustrated in Fig. 3. It is difficult to discern relationships between the variables from this without statistical analysis.

3.3. Stabilizing variance, stationarity and seasonality

As we can see from Fig. 2, there appear to be considerable differences in variance for the number of COVID-19 cases in the US over the times series. In these situations, Hyndman and Athanasopolous (2018) recommend applying a Box-Cox transformation to stabilize the variance. The value of lambda for the Box-Cox transformation was calculated as

![Fig. 1. Research process.](image-url)
0.13972 using the forecast package in R. Accordingly, a Box-Cox transformation was applied to the COVID-19 case data and the resulting time series is shown in Fig. 4, which has a considerably more stabilized variance.

The ndiffs procedure in the forecast package suggested that two orders of differences were required for stationarity. In order to assess whether the number of COVID-19 cases becomes stationary after two levels of differences, we applied the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). The KPSS Unit Root Test (mu with 5 lags) resulted in a test statistic of 0.017, well below the critical value of 0.463 for the 5% significance level. This suggests that the data set is stationary and that no further differencing in the data is required. The differenced data is shown in Fig. 4, which now appears much like white noise.

Fig. 5 displays histograms of the frequency distributions of the variables used in the analysis. Normality of the variables is not a requirement of ARIMA analysis.

In order to confirm that the time series is stationary, the autoarima procedure (Hyndman and Khandakar, 2008) was applied to the differenced case data and the residuals were examined. The result of the analysis is shown as “Model 0: Null Model” in Table 2. The procedure selected an ARIMA(3,0,2) model with zero mean as the best fit using the

Table 1
Descriptive statistics on data set.

| Variable       | Days | Daily Minimum | Daily Maximum | Daily Mean | Std. Error | Std. Deviation |
|----------------|------|---------------|---------------|------------|------------|----------------|
| Past           | 317  | 0.42%         | 3.20%         | 1.86%      | 0.0015     | 0.00260        |
| Present        | 317  | 3.31%         | 11.27%        | 6.93%      | 0.0036     | 0.00645        |
| Future         | 317  | 0.15%         | 1.90%         | 0.90%      | 0.0008     | 0.00139        |
| COVID-19 Cases | 317  | 6             | 314,093       | 73579.79   | 3928.24    | 70708.30       |
maximum likelihood procedure (suggesting no differencing in the dependent variable, since this has already been dealt with – as discussed above). A non-seasonal ARIMA(p,d,q) model is given by the equation:

$$\phi(B)(1-B)^dY_t = c + \theta(B)\epsilon_t$$  \hspace{1cm} (1)

Where $$\epsilon_t$$ refers to a white noise process, $$\mathcal{N}(0, \sigma^2)$$. B is the backshift operator, $$\phi(B) = (1 - \phi_1B - \ldots - \phi_pB^p)$$ (the autoregressive or AR components), and $$\theta(B) = (1 + \theta_1B + \ldots + \theta_qB^q)$$ (the moving average or MA components). Thus, for the resulting model with zero mean this becomes:

$$y_t = \phi_1y_{t-1} + \phi_2y_{t-2} + \phi_3y_{t-3} + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \epsilon_t$$  \hspace{1cm} (2)

Where $$Y_t=(1-B)^d Y_t$$. Three autoregressive coefficients are identified in the model, with two of them being significant, AR1 ($$\phi_1 = 0.23$$, p<.01) and AR3 ($$\phi_3 = -0.22$$, p<.001). In addition, the two moving average coefficients, MA1 ($$\theta_1 = -1.67$$) and MA2 ($$\theta_2 = 0.75$$) are both significant at the 0.1% level. Given that the data has already been differenced twice before analysis, so $$y_t=(1-B)^2 Y_t$$, the equation of the resulting model is:

$$y_t = 0.23y_{t-1} + 0.22y_{t-2} - 1.67\epsilon_{t-1} + 0.75\epsilon_{t-2} + \epsilon_t$$  \hspace{1cm} (3)

Residual diagnostics are provided in Fig. 6. Here we can see that the autocorrelation function (ACF or correlogram) identifies numerous lags that are outside of the 95% range identified by the blue dashed lines,
suggesting that this is not a white noise series. In order to confirm that this is not a false positive result, a portmanteau test was conducted – the Ljung-Box test (Ljung and Box, 1978), which is considered more accurate than the related Box-Pierce test (Box and Pierce, 1970; Box et al., 2015). The Ljung-Box $Q^*$ was 31.233, which is significant at the 0.1% level ($df = 5$, total lags used = 10), suggesting that the data is not white noise and is therefore not yet stationary. The residuals plot suggested potential weekly seasonality in case numbers; therefore, a seasonal decomposition was conducted.

Fig. 7 shows the result of decomposing the case variable based on an additive time series. As we can see from the third window, there is a clear weekly seasonal component in the data. Therefore, this component was removed (subtracted) from the differenced time series (see Fig. 8) and the autoarima procedure was conducted on the revised data set. The resulting model is shown as “Model 0d: De-seasonalized Null Model” in Table 2. This is an ARIMA$(0,0,2)(0,0,1)[7]$ model. The general form of a seasonal ARIMA$(p,d,q)(P,D,Q)[m]$ model is:

$$\Phi(B^m)(1-B)^dY_t = c + \Theta(B^m)(1+\theta_1)\varepsilon_t$$

where $m$ is the time span of the seasonal pattern, $\Phi(B^m) = (1 - \Phi_1B^m - \cdots - \Phi_PB^{Pm})$ (seasonal AR components), and $\Theta(B) = (1 + \Theta_1B^m + \cdots + \Theta_QB^{Qm})$ (seasonal MA components). Thus, Model 0d is equivalent to the model:

$$\Phi(B^m)(1-B)^dY_t = c + \Theta(B^m)(1+\theta_1)\varepsilon_t$$

This new model retained the moving average terms $\text{MA}_1$ ($\theta_1 =$ --

Table 2
Null models.

| Term  | Null Model | Model 0d: De-seasonalized Null Model |
|-------|------------|--------------------------------------|
| $AR_1$ | 0.23** (0.07) |                                      |
| $AR_2$ | 0.00 (0.06)   |                                      |
| $AR_3$ | -0.22*** (0.06) |                                    |
| $MA_1$ | 0.17*** (0.05) | 0.61*** (0.05)                        |
| $MA_2$ | -1.07*** (0.06) | -1.56*** (0.04)                      |
| $SMA_1$| 0.68         | 0.53                                 |
| $n$   | 315         | 315                                  |

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. 

Fig. 6. Residual diagnostics for null model.

Fig. 7. Decomposition of additive time series.
and MA2 ($\theta_2 = 0.61$) at similar levels and at the 0.1% level of significance. However, a new weekly seasonal moving average term was introduced into the model, SMA1 ($\Theta_1 = 0.17$), which is significant at the 1% level. Given that $y_t = (1 - B)^d Y_t$, the equation of the new model can be simplified as:

$$ y_t = \varepsilon_t $$

where $k$ is the number of predictors in the model and $\eta_t$ is the error series that is assumed to follow an ARIMA model. Thus, we have two error terms: the error from a regression model, $\eta_t$, and the error from the ARIMA model, $\varepsilon_t$. Whilst ARIMA model errors are assumed to be white noise, regression model errors are not, and are used for purposes of prediction.

The `autoarima` procedure selects the model that fits best according to the ARIMA errors and differences any variables that need it (such as the independent variables in our models). The AICc is computed for the final model, which can then be used to determine which predictors in candidate models should be used. The procedure should be run for all subsets of predictors to be considered, and the model with the lowest AICc value is then selected (Hyndman and Athanasopolous, 2018).

Statistical modelling applied seven candidate ARIMA models to the data: three single predictor models (Model 1: Past, Model 2: Present, and Model 3: Future), three dual predictor models (Model 4: Past & Present, Model 5: Present & Future, and Model 6: Past & Future), and the full model with all three predictors (Model 7). The specific models tested using dynamic regression were:

- **Model 1:**
  $$ y_t = \beta_0 + \beta_1 t + \eta_t $$

- **Model 2:**
  $$ y_t = \beta_0 + \beta_1 t + \eta_t $$

- **Model 3:**
  $$ y_t = \beta_0 + \beta_1 t + \eta_t $$

3.4. Testing and Evaluating the dynamic regression Models and hypotheses

Once the time series had been prepared for dynamic regression, a number of candidate models were examined via the `autoarima` procedure. Dynamic regression involves estimating a regression using ARIMA errors, but requires that the variables are stationary, as we have confirmed in section 3.2. The general form of a dynamic regression model measured with ARIMA errors is given by:

$$ y_t = \beta_0 + \beta_1 x_t + \cdots + \beta_k x_{tk} + \eta_t $$

and

$$ \Phi(B^m)\phi(B)(1 - B)^d(1 - B)^c \eta_t = c + \Theta(B^m)(1 + \theta_1) \varepsilon_t $$

where $k$ is the number of predictors in the model and $\eta_t$ is the error series that is assumed to follow an ARIMA model. Thus, we have two error terms: the error from a regression model, $\eta_t$, and the error from the ARIMA model, $\varepsilon_t$. Whilst ARIMA model errors are assumed to be white noise, regression model errors are not, and are used for purposes of prediction.
Model 4:
\[ y_t = \beta_0 + \beta_1 \text{past} + \beta_2 \text{present} + \eta_t \] (12)

Model 5:
\[ y_t = \beta_0 + \beta_1 \text{present} + \beta_2 \text{future} + \eta_t \] (13)

Model 6:
\[ y_t = \beta_0 + \beta_1 \text{past} + \beta_2 \text{future} + \eta_t \] (14)

Model 7:
\[ y_t = \beta_0 + \beta_1 \text{past} + \beta_2 \text{present} + \beta_3 \text{future} + \eta_t \] (15)

Fit metrics (AICc, BIC and Log-Likelihood) were examined to identify the model that fits best with the data. The final model was then examined using residual diagnostics and the portmanteau test. The selected model was then further examined using a z-test of the coefficients in the full dynamic regression model. The p-value of the z-test coefficients was then used as the basis for hypothesis testing.

4. Results of dynamic regression modelling

The seven candidate models were tested using the autoarima algorithm in the forecast package and in each case an ARIMA(0,0,2)(0,0,1) [7] model was selected by the procedure. Results of the model comparison are shown in Table 3.

Fig. 10 shows a comparison of model fit for the three single predictor variable models (Models 1 to 3), three dual-predictor models (Models 4 to 6) and the full three-variable ARIMA model (Model 7). As we can see, the fit for the dual model with the past and present predictor variables appears superior for two of the metrics (AIC/AICc and BIC, although the margin is very small for AIC/AICc), while the full model with three variables is marginally better for the Log-Likelihood metric. The Past, Present, Future and Present & Future variables is marginally better for the Log-Likelihood metric. The Past, Future, and Full models (Models 1 to 3), three dual-predictor models (Models 4 to 6) and the full three-variable ARIMA model (Model 7) were considered to be Model 4, with past and present temporal focus predictors.

The statistical analyses for hypothesis testing using the dynamic linear regression are also shown in Table 3. This provides the significance level of the models’ terms from a z-test of the coefficients used in the ARIMA models. As we can see, Model 4 has two significant moving averages at the p < .001 level, MA1 and MA2, and a small seasonal moving average that is significant can the p < .001 level, SMA1. This indicates that there is a small but significant amount of residual seasonality that is picked-up by the automatic ARIMA procedure.

Regarding the temporal focus predictor variables, the coefficient test show that past focus has a direct and significant effect on the number of COVID-19 cases at the 0.1 percent level (\( \beta_1 = 4.95, p < 0.001 \)). This provides support for Hypothesis 1. Further, the z-test of the coefficient for present temporal focus shows that it has a more significant but smaller (in absolute terms) inverse impact on the number of COVID-19 cases at the 0.1 percent level (\( \beta_2 = -1.35, p < 0.001 \)). Thus, support is also provided for Hypothesis 2. However, the predictor for future temporal focus does not appear in this model and therefore no support is offered for Hypothesis 3. This is likely to be due to insufficient data for temporal focus in the data set, and furthermore, Model 7 shows an extremely high standard error for future focus.

In other words, the difference in the differences in the number of COVID-19 cases can be partly explained by the temporal focus of citizens, measured through a big data set of tweets as a proxy of the nation’s overall perspective. In terms of the predictive quality of the final model, the squared correlation between the fitted values of Model 4 and the dependent variable used in the analysis (similar to R-squared) is 0.76, suggesting a good predictive value of the model; 76% of the value of the data is captured by the fitted model.

5. Discussion and conclusions

This research suggests that temporal focus, measured through big
This aspect in the time window. The limited data could potentially be due to a lack of data measuring temporal focus, and this is likely to be due to a lack of data on future temporal focus and more data is needed to support the findings of Sobol-Kwapinska et al. (2020) relating to a positive correlation between a present temporal focus and compliance with public health regulations concerning COVID-19. More generally, it supports studies that find that a present focus tends to have a positive impact (e.g., Rush and Grouzet, 2012; Tseferifi et al., 2017). This would appear consistent with a Carpe Diem time perspective (Sobol-Kwapinska et al., 2020; Tseferidi et al., 2017). Unfortunately, the study did not find that a future temporal focus had a significant relationship with infection rates. This is a surprising finding that is likely to be due to a lack of data. Future focus deserves greater scrutiny in future studies investigating COVID-19 and infection rates using big data analytics.

This study contributes useful findings that are relevant to the practice of public health policy. Improving citizens’ response to public health measures requires a better understanding of the determinants of behaviors to understand which individuals are likely to flout the rules and which are likely to follow them. The understanding of temporal focus as a driver of infection enables more effective development of two aspects of public health policy. First, by identifying these significant determinants of changes in COVID-19 cases, it provides additional metrics to improve the development of epidemiological models to better understand the spread of the disease (and other diseases). Second, by understanding the inverse relationship of present focus and the direct relationship of past focus that have been found in numerous other studies. In the context of the pandemic, past temporal focus has a direct relationship with infection rates. On the other hand, a strong present focus has an inverse relationship with infection rates. This directly supports the findings of Sobol-Kwapinska et al. (2020) relating to a positive correlation between a present temporal focus and compliance with public health regulations concerning COVID-19. More generally, it supports studies that find that a present focus tends to have a positive impact (e.g., Rush and Grouzet, 2012; Tseferifi et al., 2017). This would appear consistent with a Carpe Diem time perspective (Sobol-Kwapinska et al., 2020; Tseferidi et al., 2017). Unfortunately, the study did not find that a future temporal focus had a significant relationship with infection rates. This is a surprising finding that is likely to be due to a lack of data. Future focus deserves greater scrutiny in future studies investigating COVID-19 and infection rates using big data analytics.

This study has a number of limitations. The data set contained inadequate data on future temporal focus and more data is needed to measure the impact of this variable. It is possible that the content of tweets may be distinct from an individual’s actual temporal orientation (e.g., the nature of tweeting may be a more immediate/present oriented activity, where people are tweeting about current happenings). At the time of this research, although vaccines have been developed and are being administered in the US and elsewhere, for the time being, the...
Social Science & Medicine 280 (2021) 114057

12

Griva, F., Tsefekidri, S.-L., Anagnostopoulos, F., 2015. Time to get healthy: associations of time perspective with perceived health status and health behaviors. Psychol. Health Med. 20 (1), 25–33.

Hofstede, G., Hofstede, G.J., Minkov, M., 2010. Cultures and Organizations: Software of the Mind, third ed. McGraw-Hill, New York.

Hollanders, D., Vliegenthart, R., 2008. Telling what yesterday’s news might be tomorrow: modeling media exposure in cross-national surveys. Comput. Hum. Behav. 24 (4), 1257–1266.

Hyndman, R.J., Athanasopoulos, G., 2018. Forecasting: Principles and Practice. OTexts. Melbourne. OTexts.com/fpp2, second ed. 4th September, 2020.

Ireland, M.E., Schwartz, H.A., Chen, Q., Ungar, L.H., Albarracin, D., 2015. Future-oriented tweets predict lower county-level HIV prevalence in the United States. J. Health Psychol. 20 (1), 15–24.

Jovanovice, A., Milicevic, N., 2020. Optimism-pessimism, conspiracy theories and general trust as contributors to COVID-19 related behavior: a cultural study. Pers. Indiv. Differ. 167, 110216.

Kelly, J.J., McGrath, J.E., 1988. On Time and Method. Sage Publications, Newbury Park, CA.

Keough, K.A., Zimbardo, P.G., Boyd, J.N., 1999. Who’s smoking, drinking, and using drugs? Time perspective as a predictor of substance use. Basic Appl. Soc. Psychol. 21, 119–124.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? J. Econom. 51 (1–3), 159–178.

Laurore-Martinez, D., Trujillo, C.A., Unda, J., 2017. Time perspective and age: a review of age associated differences. Front. Psychol. 8, 101. https://doi.org/10.3389/fpsyg.2017.01011 accessed 10th February, 2021.

Li, H., 2018. A future-minded lark in the morning: the influence of time-of-day and chronotype on metaphorical associations between space and time. Metaphor Symbol 33, 48–57.

Li, S., Wang, Y., Xue, J., Zhao, N., Zhu, T., 2020. The impact of COVID-19 epidemic declaration on psychological consequences: a study on active Weibo users. Int. J. Environ. Res. Publ. Health 17 (6), 2032.

Li, H., Cao, Y., 2021. In times of illness: covid-19 threat temporal focus and implicit space-time mappings. Pers. Indiv. Differ. 171, 110561.

Lijung, G.M., Box, G.E.P., 1978. On a measure of a lack of fit in time series models. Biometrika 65 (2), 297–303.

Makhanovska, A., Shepherd, M., 2020. Behavioral immune system linked to responses to the threat of COVID-19. Pers. Indiv. Differ. 167, 1–7.

Milfont, T.L., Wilson, J., Döniz, P., 2012. Time perspective and environmental engagement: a meta-analysis. Int. J. Psychol. 47, 325–334.

Papoulis, A., Pillai, U., 2002. Probability, Random Variables, and Stochastic Processes. McGraw-Hill, New York.

Park, G., Schwartz, H.A., Sap, M., Kern, M.L., Weingarten, E., Eichstaedt, J.C., Berger, J., Stillwell, D.J., Kosinski, M., Ungar, L.H., Seligman, M.E.P., 2017. Living in the past, present, and future: measuring temporal orientation with language. J. Pers. 85, 270–282.

Pennebaker, J.W., Booth, R.J., Boyd, R.L., Francis, M.E., 2015a. Linguistic Inquiry and Word Count: LIWC2015. Pennebaker Conglomerates, Austin, TX. www.LIWC.net.

Pennebaker, J.W., Boyd, R.L., Jordan, K., Blackburn, K., 2015b. The Development and Psychometric Properties of LIWC2015. University of Texas at Austin, Austin, TX.

Przepiorka, A., Blachnio, A., 2016. Time perspective in Internet and Facebook addiction. Comput. Hum. Behav. 60, 13–18.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88, 879–903.

Rappaport, H., 1990. Marking Time. Simon & Schuster, New York.

Rothspan, S., Read, S.J., 1996. Present versus future time perspective and HIV risk among heterosexual college students. Health Psychol. 15, 131–134.

Rubin, J., Grosser, F.M.E., 2012. It is about time: daily relationships between temporal perspective and well-being. J. Posit. Psychol. 7 (5), 427–442.

Sergent, J., Padilla, R., 2021. The U.S. COVID-19 death toll now exceeds 406,000. That’s more than the number of Americans who died in WWII. USA Today, January 19, 2021. 5th February, 2021. https://usatoday.com/in-depth/news/politics/2021/01/19/ covid-19-deaths-americans-dying-faster-than-our-world-did-wwii/6602717002/.

Shin, Y., 2017. Time Series Analysis in the Social Sciences: the Fundamentals. University of California Press, Oakland, CA.

Shipp, A.J., Edwards, J.R., Schurer Lambert, L., 2009. Conceptualization and Psychometric Properties of LIWC2015. University of Texas at Austin, Austin, TX.

Stillwell, D.J., Kosinski, M., Ungar, L.H., Seligman, M.E.P., 2017. Living in the past, present, and future: measuring temporal orientation with language. J. Pers. 85, 270–282.

Sobol-Kwapinska, M., Jankowski, T., 2016. Positive time. Balanced time perspective and optimism-pessimism, conspiracy theories and general trust as contributors to COVID-19 related behavior: a cultural study. Pers. Indiv. Differ. 167, 110216.

Soto, M., Matthews, G., Postek, S., Zimbardo, B.G., Bitner, J., 2014. How we feel is a number of time: relationships between time perspectives and mood. J. Happiness Stud. 15, 809–827.
Stolarski, M., Matthews, G., 2016. Time perspectives predict mood states and satisfaction with life over and above personality. Curr. Psychol. 35, 516–526.

Tankovska, H., 2021. Twitter usage penetration in the United States 2020, by age group. March 24th, 2021. https://www.statista.com/statistics/227175/daily-us-twitter-users-by-age-group/.

Trope, Y., Liberman, N., 2003. Temporal construal. Psychol. Rev. 110, 403–421.

Tsai, R.S., 2010. Analysis of Financial Time Series. John Wiley & Sons, Hoboken, NJ.

Tseferidi, S.I., Griva, F., Anagnostopoulos, F., 2017. Time to get happy: associations of time perspective with indicators of well-being. Psychol. Health Med. 22 (5), 618–624.

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C.S., Ho, R.C., 2020. Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. Int. J. Environ. Res. Publ. Health 17 (5), 1729.

Wilson, I., Hartly, S.R.A., Fenn, B., 2006. A case study of sample design for longitudinal research: young lives. Int. J. Soc. Res. Methodol. 9, 351–365.

Yanovitzky, I., VanLeer, A., 2007. Time series analysis. Traditional and contemporary approaches. In: Hayes, A.F., Slater, M., Snyder, L.B. (Eds.), The SAGE Sourcebook of Advanced Data Analysis Methods for Communication Research. Sage Publications, Thousand Oaks, CA, pp. 89–124.

Zajenkowski, M., Jonason, P., Lenarska, M., Kozakiewicz, Z., 2020. Who complies with the restrictions to reduce the spread of COVID-19? Personality and perceptions of the COVID-19 situation. Pers. Indiv. Differ. 166, 1–6.

Zaleski, Z., Sobol-Kwapinska, M., Przepiorka, M., 2017. Development and validation of the dark future scale. Time Soc. 28 (1), 107–123.

Zhang, J.W., Howell, R.T., 2011. Do time perspectives predict unique variance in life satisfaction beyond personality traits? Pers. Indiv. Differ. 50, 1261–1266.

Zimbardo, P.G., Boyd, J.N., 1999. Putting time in perspective: a valid, reliable individual-differences metric. J. Pers. Soc. Psychol. 77 (6), 1271–1288.