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Threshold of Depression Measure in the Framework of Sentiment Analysis of Tweets: Managing Risk during a Crisis Period Like the COVID-19 Pandemic

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Abstract: The COVID-19 pandemic has had a devastating impact on the world. The surge in the number of daily new cases and deaths around the world and in South Africa, in particular, has increased fear, psychological breakdown, and uncertainty among the population during the COVID-19 pandemic period, leading many to resort to prayer, meditation, and the consumption of religious media as coping measures. This study analyzes social media data to examine the perceptions and attitudes of the South African community toward religion as well as their well-being appreciation during the COVID-19 period. We extract four sets of tweets related to COVID-19, religion, life purpose, and life experience, respectively, by users within the geographical area of South Africa and compute their sentiment scores. Then, a Granger causality test is conducted to assess the causal relationship between the four time series. While the findings reveal that religious sentiment scores Granger-causes life experience, COVID-19 similarly Granger-causes life experience, illustrating some shifts experienced within the community during the crisis. This study further introduces for the first time a Threshold of Depression measure in the sentiment analysis framework to assist in managing the risk induced by extremely negative sentiment scores. Risk management during a period of crisis can be a hectic task, especially the level of distress or depression the community is experiencing in order to offer adequate mental support. This can be assessed through the Conditional Threshold of Depression which quantifies the threshold of depression of a community conditional on a given variable being at its Threshold of Depression. The findings indicate that the well-being indicators (life purpose and life experience) provide the highest values of this threshold and could be used to monitor the emotions of the population during periods of crisis to support the community in crisis management.

Keywords: well-being; spirituality index; threshold of depression; sentiment analysis

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1. Introduction

The COVID-19 pandemic has had a devastating impact in the world. As reported by Africa Centers for Disease Prevention and Control, by April 2020, in the sub-Saharan region, South-Africa was the hardest-hit country with 1686 cases and 12 deaths. Among 44 countries of the WHO African Region with available data, South Africa had the highest mortality rate during the first wave between May and August 2020, at 33.3 deaths recorded per 100,000 people. In 2022 alone, the confirmed cases of COVID-19 exceeded 406 million worldwide, with the number of confirmed deaths in the region of 5.79 million. Judging by the viral transmission and positivity rate, it was clear that the COVID-19 safety measures, especially vaccination for the coronavirus, practicing physical distancing, and mask-wearing, helped in reducing the severe health and economic impact of COVID-19. The confirmed cases of COVID-19 varied from one country to another. For example, as of March 2022 South Africa recorded more than 3.7 million cases and nearly 100,000 COVID-19 deaths. The surge in the number of daily new cases and deaths around the world, and in South Africa in particular, has increased fear, psychological breakdown, and uncertainty among the population during the COVID-19 pandemic period, leading many to resort to prayer, meditation, and consumption of religious media as coping measures.

While the existing studies have constructed a spiritual well-being index and extensively studied the relationship between spirituality and health outcomes (Büssing et al. 2010; Hvidt et al. 2019) relying on surveys or interviews, they are subject to many hurdles. Perhaps the key challenge is that surveys are too labor-intensive and time-consuming. In view of this empirical concern, there has been a growing interest in exploring big data via online platforms. Extracting data from social media platforms (such as Twitter) allow scholars and policy-makers alike to obtain real-time evidence/data to assess social attitudes on various topical issues, and save a lot of time and cost (Hollander et al. 2016).

Among the popular social networks are Facebook, YouTube, and Twitter. Through these networks, users are able to interact with each other through post messages in the forms of texts, images, and videos (Jansen et al. 2009; Kharde and Sonawane 2016). Microblogging services such as Twitter have become the best-known and the most commonly used platforms and have evolved to become significant sources of different types of information (Selvaperumal and Suruliandi 2014). Twitter allows users to share real-time, short, and simple messages called tweets (Singh and Kumari 2016). This provides a rich source of data that is used in the fields of opinion mining and sentiment analysis. Most state-of-the-art studies have used sentiment analysis to extract and classify information about the opinions expressed on Twitter concerning several topics. Sentiment analysis has been applied in various fields of study such as healthcare (Yang et al. 2016), behavioral finance (Huerta-Sanchez and Escobari 2018), political science (Mestre-Mestre 2021), and cognitive computing (Li et al. 2018).

Given the concise language used in tweets, and the ability to obtain information about public opinion by analyzing Twitter data and automatically classifying their sentiment polarity, Twitter sentiment analysis has brought significant insight into many research areas. Currently, many lexicon-based sentiment analyzers, such as Linguistic Inquiry and Word Count (LIWC), TextBlob, Valence Aware Dictionary, and sEntiment Reasoner (VADER) offer the means of extracting advanced features from texts. However, most of these tools require some programming knowledge. VADER is a less resource-consuming sentiment analysis model that uses a set of rules to specify a mathematical model without explicitly coding it. As compared to machine learning models, it does need vast amounts of training data and does not suffer severely from a speed-performance tradeoff. VADER's resource-efficient approach helps us to decode and quantify the emotions contained in streaming media such as text, audio, or video. This study has shown that VADER performs as well as individual human raters at labeling the sentiment of a text. The reason behind this is the sensitivity of VADER (Gilbert and Hutto 2014) to both polarity (whether the sentiment is positive or negative) and intensity (how positive or negative is the sentiment) of emotions. In the present work, VADER is used to determine the polarity of tweets and to classify them according to multiclass sentiment analysis.

VADER normalizes the scores between -1 (most extreme negative) and +1 (most extreme positive), hence sharing a similar pattern to the financial returns series. While in the financial context, a positive return represents gain and a negative return represents loss, in sentiment analysis, a positive score represents positive emotions, and a negative score represents negative emotions. This study analyzes social media data to examine the perceptions and attitudes of the South African community toward religion as well as its well-being appreciation during the COVID-19 period. To this end, we consider four variables for our analysis. These consist of tweets related to COVID-19, religion, life purpose, and life experience by users within the geographical area of South Africa. Hidalgo et al. (2010) consider six factors among which is "Life purpose" (having goals that direct one's life) to assess psychological well-being, and found that life purpose has higher scores among young people. In the assessment of well-being, Stiefel et al. (2020) consider factors such as life satisfaction, life experience, life purpose, and physical health, among others, and hence our choice of life purpose and life experience in this study.

While the relationship between spirituality and health outcomes is gaining the attention of economists, social psychologists, and other scholars working in related fields, little is known about the impact of spiritual well-being on the life of people during the COVID-19 pandemic period (with the exception of few recent studies tackling fairly related issues, such as Lindner et al. (2022), on the relations between different lockdown restrictions and mental health issues; Bianchi et al. (2021) on the long-term impact of the COVID-19 unemployment shock on life expectancy and mortality rates; Ruiz Sánchez (2022) on COVID-19 and suicides; Böckerman and Ilmakunnas (2008), on unemployment and self-assessed health). Yet, many COVID-19 survivors, including those who lost a loved one during the COVID-19 pandemic, identify spiritual forms of coping (such as prayer and hope) as a major factor in their health and well-being (Biancalani et al. 2022). Indeed spirituality is not only used to cope with COVID-19, but it has also been used to cope with various life challenges/health shocks such as depression (Stefa-Missagli et al. 2020), heart failure (Bekelman et al. 2007), binge-trait eaters/eating disorders (King et al. 2018), suicide attempts (Heidari et al. 2019), emotional maladjustment, and chronic pain diseases and cancer (Büssing et al. 2010; Hvidt et al. 2019).

Stefa-Missagli et al. (2020) used backward stepwise multiple regressions and the Mini International Neuropsychiatric Interview to explore the possible relationship between suicide and spirituality in Italy and Austria. The findings indicate that in general for psychiatric patients, spirituality and religiosity were significantly related to several suicidal behaviors such as suicidal ideation, the intensity of ideation, suicidal behavior, and actual suicide attempts. The authors conclude that various aspects of religious well-being were negatively related to suicide dimensions.

King et al. (2018) used stepwise regression and a convenience sample of 55 African American college women to study the extent to which ethnic identification, spirituality, and internalization of the thin ideal are related to decreased body dissatisfaction and eating disordered behaviors. Various measures (such as the 'Eating Attitudes Test, Eating Disorders Inventory, Multigroup Ethnic Identity Measure, Sociocultural Attitudes toward Appearance Questionnaire, Life Regard Index-R, and Spiritual Transcendence Index') were performed, and the results reveal a positive association between eating disordered behaviors, body dissatisfaction, and internalization of the thin ideal. Moreover, they observed a positive relationship between spiritual transcendence and body dissatisfaction.

A study by Rippentrop et al. (2005) looked at the relationship between spirituality, physical health, and mental health in 122 patients with chronic musculoskeletal pain. Using hierarchical multiple regression, they found evidence to suggest a significant association between spirituality and physical and mental health. Specifically, they found that prayer, meditation, and consumption of religious media helps to ameliorate physical health outcomes, suggesting that some of the patients used spirituality as a coping mechanism. Other coping measures (such as relaxation, diversion, and exercise) other than spiritual forms have been used as well to cope with chronic pain (Keefe et al. 1997, 2000). As noted earlier, although some studies focus on the relationship between spirituality and health outcomes, the impact of spiritual well-being on the life of people during the COVID-19 pandemic period is often ignored. First, this topic becomes more urgent and important in the current context of many people diagnosed with COVID-19 that have a significant risk of developing anxiety or entering into a depression state. Large bank losses in the mid-1980s brought an increasing interest in financial risk management. Many statistical techniques to measure and manage market risk have since emerged, including the popular Value at Risk (VaR). The publication of JP Morgan's RiskMetrics Technical Document in 1996 introduced VaR as a comprehensive, unifying statistical market risk measure (Morgan 1996). The VaR measure at a given confidence level (q) is the value such that the probability of a loss smaller than that value (VaR) occurring is $(1 - q)$.

In the context of sentiment analysis, though we are not dealing with money, this risk measure concept can be redefined to capture the risk of entering into a depression state of a given population. Considering this, our key contribution is that we introduce a distress measure called Threshold of Depression (ToD). It measures, based on sentiment scores, the score beyond which lies a depression zone for a given variable under study, which should raise an alarm. We proceed by computing the Conditional Threshold of Depression (CToD) which measures the ToD of a population given that one of the variables under study is at its ToD. We further compute the Delta Conditional Threshold of Depression (ΔCTOD) which captures the contribution of each variable to the depression of the population under study. The results reveal that the COVID-19 variable has the lowest Threshold of Depression while the well-being variables (life experience and life purpose) have the highest. This may indicate that the population was able to cope quite well with the pandemic with the aid of spirituality. Furthermore, we found that the well-being variables (life experience and life purpose) capture quite adequately the state of mind of the population and could be used as happiness indicators.

In addition to this Threshold of Depression measure, this paper uses the Granger causality model (GCM) derived from the multivariate vector autoregressive (VAR) model to explore the interdependence between the spirituality well-being index, COVID-19, life experience, and life purpose sentiment scores. Previous studies have used Granger causality to reveal an interdependent structure in multivariate time series (Lutkepohl 2005; Kirchgassner and Wolters 2007; Faes et al. 2012). As initially introduced by Granger (Granger 1969), a variable X Granger-causes another variable Y if the prediction of Y is enhanced when X is included in the prediction model for Y.

In summary, this study aims at answering the following research questions: (a) were people in South Africa much more positive about religion during the COVID-19 pandemic period? (b) How was their attitude toward life during the COVID-19 pandemic period? (This will be assessed through life purpose and life experience factors). (c) What factor systematically provides us with a Threshold of Depression value likely to be used as a barometer of distress within the community of South Africa during the crisis period?

The findings show that, at a 95% confidence level, the spirituality index Granger-causes life experience. Meaning, the level of spirituality/religiosity has an impact on the quality-of-life experience. This is in line with Křeménková and Novotny (2015) who analyzed how much faith affects life's meaningfulness through an existential scale (ES) questionnaire. When lowering the confidence level to 90%, we found that COVID-19 Granger-causes life experience. Thus, the negative impact of COVID-19 is dynamically being corrected by the spirituality strategy to lower the level of depression among the population.

The rest of the paper is organized as follows: Section 2 describes the suggested methodology. Section 3 discusses the results derived from the methodology. Finally, Section 4 closes with a summary of the key findings and guidelines for future potential research directions.

2. Methodology

2.1. Valence Aware Dictionary and Sentiment Reasoner (VADER)

Social media technologies aim at allowing people to express and share their thoughts and opinions about life events. They are enormous sources of information for companies to monitor the public opinion about their products. They also give to interested parties a pool of information on public thoughts and opinions concerning various topics, such as predictions, reviews, elections, and marketing. Recently, sentiment analysis has attracted the attention of researchers in these fields.

VADER (Gilbert and Hutto 2014) assigns a score (known as Valence Score) to a word under evaluation on a scale from -4 to +4, where -4 stands for the most 'Negative' sentiment, +4 for the most 'Positive' sentiment, and 0 represents 'Neutral' Sentiment. The compound score is therefore computed as the sum of positive, negative, and neutral scores which is then normalized between -1 (most extreme negative) and +1 (most extreme positive) using the function

$$\frac{x}{\sqrt{x^2+\alpha}}$$

where x = sum of valence scores of constituent words, and α = normalization constant (default value is 15). With the compound score, positive, neutral, and negative sentiments can be identified using the following scale:

Positive sentiment: (compound score ≥ 0.05);
Neutral sentiment: (-0.05 < compound score < 0.05);
Negative sentiment: (compound score ≤ -0.05).

In this study, we will first compute the sentiment scores of each of the tweets related to religion/spirituality, life purpose, life experience, and COVID-19 from users in the geographical area of South Africa during the period 11 February 2020 to 31 December 2021. We will refer to the compound scores of religion/spirituality, and life purpose or life experience as the spirituality index and well-being index, respectively. Life purpose or life experience captures the overall emotions of the population through which their well-being can be assessed. Exploring the interdependence relationship between these indices and COVID-19 sentiment scores may assist in understanding how people relate to God in times of crisis, especially during the COVID-19 pandemic, given that people used spirituality as a coping mechanism, as suggested by Rippentrop et al. (2005). To assess this, we will use the Granger causality model (GCM) derived from the multivariate vector autoregressive (VAR) model.

2.2. Vector Auto-Regressive (VAR) Model

VAR models belong to a class of multivariate linear time series models called vector autoregression moving average (VARMA) models. These models are well suited for modeling the movements of several stationary time series simultaneously, measuring the delayed effects among the response variables, as well as the effects of exogenous series on variables in the system. In the VAR model, each variable is modeled as a linear combination of past values of itself and the past values of other variables in the system.

The dataset consists of the following four time series spanning the period from 11 February 2020 to 31 December 2021:

RELI: Religiosity/spirituality index.
COVID: COVID-19 sentiment scores.
LEXP: Life experience sentiment scores.
LPURP: Life purpose sentiment scores.

2.3. Conditional Threshold of Depression (CToD)

In the geographical region R, consider n variables $R_1, R_2, \ldots, R_n$ with sentiment scores $r_1, r_2, \ldots, r_n$, respectively. Let r_c be the weighted average of the sentiment scores $r_1, r_2, \ldots, r_n$, that is, $r_c = \sum_{i=1}^{n} w_i r_i$ where w_i is the weight assigned to r_i.

Let r_c be a random variable with distribution function F.

The Threshold of Depression at confidence level q for r_i, ToD_q^i is s if the probability for the sentiment score to be less than or equal to s is $1-q$.

$$\begin{aligned} ToD_q^i &= inf\{s \in [-1,1] \ : P[-r_i \geq s] \geq 1-q\} \\ &= inf\{s \in [-1,1] \ : F(-s) \geq 1-q\} = -F^{-1}(1-q) \end{aligned}$$

where $0 < q < 1$ is the confidence level.

Suppose that $r_i \sim N(\mu, \sigma^2)$. Denote by Φ the distribution function of the standard normal distribution. Then,

$$ToD_q^i = \Phi^{-1}(1-q)\sigma - \mu$$

Let $r_c = \sum_{i=1}^{n} w_i r_i$. We define the Conditional Threshold of Depression $CToD_q^{c|i}$ with confidence level q as the ToD_q^c conditional upon variable r_i being at its Threshold of Depression. It is the quantile of the conditional probability distribution

$$P(r_c \leq CToD_q^{c|i} \mid r_i = ToD_q^i) = 1-q$$

In this study, $n = 4$, and r_1, r_2, r_3, and r_4 stand respectively for RELI, COVI, LPURP, and LEXP.

In addition, the contribution of a variable i to depression in the population is denoted by $\Delta CToD_q^{c|i}$ and is given by the following formula:

$$\Delta CToD_q^{c|i} = \left(CToD_q^{c|i} - CToD_{0.5}^{c|i}\right)/CToD_{0.5}^{c|i}$$

where $CToD_{0.5}^{c|i}$ represents the normal/median state of the population.

This measure can be used to rank the variables from less to highly depressive indicators.

3. Empirical Results and Analysis

3.1. Descriptive Statistics

From Table 1, the level of dispersion of variation is fairly the same, around 0.5 for the four series. The medians for RELI and COVI are all zero, as compared to LPURP and LEXP with medians sitting at around 0.5. The median is the most informative measure of the central tendency for skewed distributions or distributions with outliers. In skewed distributions, more values fall on one side of the center than the other, and the mean, median, and mode all differ from each other. One advantage of the median is that it is not influenced much by extreme outliers or non-symmetric distributions of scores, making it a true reflection of the state of the variable under examination. Based on this measure, we can infer that within our geographical area of analysis, the population has remained positive in terms of their life purpose and life expectation. Though not quite negative in terms of their spirituality, they present a kind of neutral sentiment toward their religious belief. The sentiment score intervals for RELI, COVI, LPURP, and LEXP are $[-0.98, 0.99]$, $[-0.99, 0.99]$, $[-0.95, 0.99]$ and $[-0.98, 0.99]$, respectively.

Table 1. Descriptive statistics.

	RELI	COVI	LPURP	LEXP
mean	0.1057	0.0616	0.3853	0.3363
std	0.5228	0.5069	0.5154	0.5419
min	−0.9855	−0.9989	−0.9591	−0.9811
25%	−0.2943	−0.3182	0.0000	0.0000
50%	0.0000	0.0000	0.5423	0.5070
75%	0.5423	0.4767	0.8360	0.8020
max	0.9925	0.9999	0.9943	0.9946

Note: "mean" represents the mean of each variable; "std" represents the standard deviation; "min" is the minimum score; "25%" is the 25th percentile; "50%" is the 50th percentile or the median; "75%" is the 75th percentile; "max" represents the maximum score.

Figure 1 shows the dynamics of the sentiment scores of each series. As displayed, they are not constant over time and exhibit frequent oscillation between positive and negative, particularly for the spirituality index, life purpose, and life expectation. The sentiment scores for COVID-19 show some extreme spikes at the beginning of the pandemic illustrating the confusion and high uncertainty it brought. Then, immediately after that short period, a relatively constant trend is witnessed depicting various segments of waves and implied regulations experienced within the population. This could also be a quick adaption through a coping mechanism or resilience. Has religion or spirituality as a coping mechanism played a role in this adaption? If positive at all, how has this been translated into the well-being of the population? We will assess the well-being of the population through the life experience and life purpose indicators.

One way to assess the interconnectedness between these variables is through the Granger causality test. As initially introduced by Granger (Granger 1969), a variable V Granger-causes another variable W if the prediction of W is enhanced when V is included in the prediction model for W.

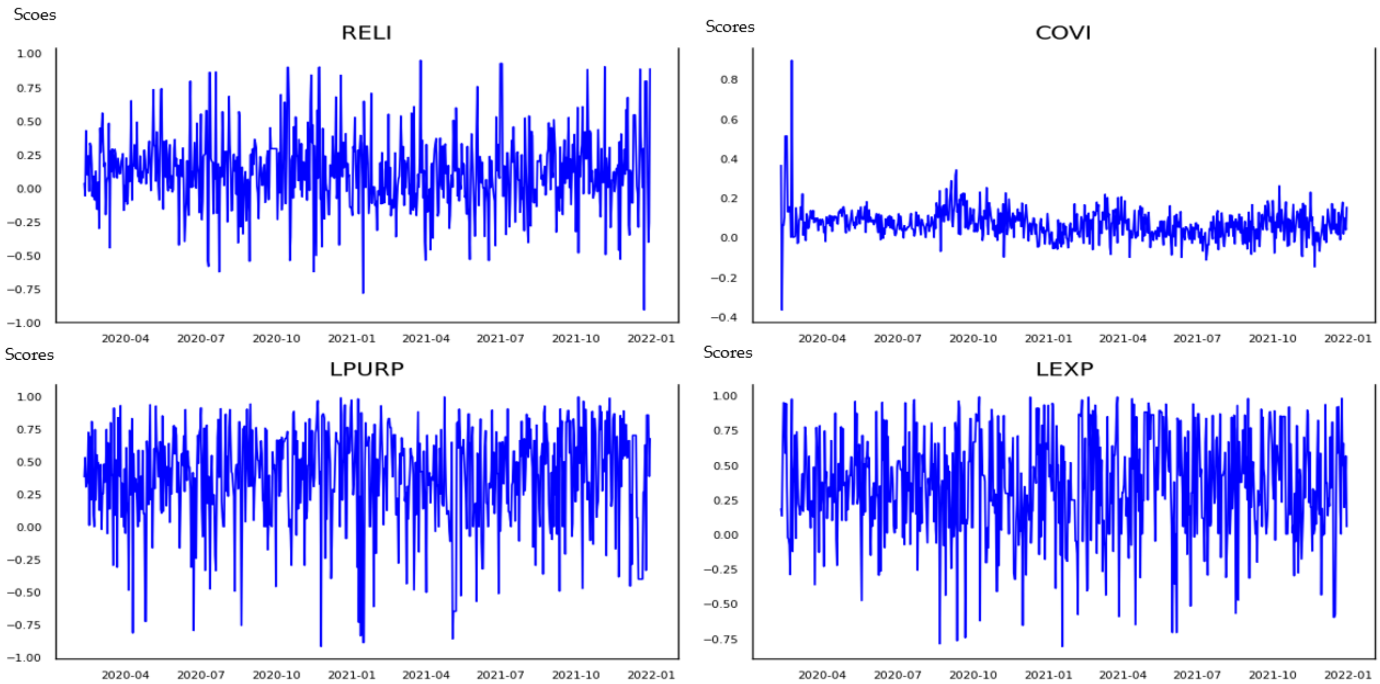

Figure 1. Sentiment scores. Notes: In these plots, the vertical axes represent the sentiment scores and the horizontal axes represent the dates in the sequence of three-month intervals.

In the next step, we will check for causality amongst these series using the Granger causality test and the cointegration test.

3.2. Testing Causation Using the Granger Causality Test

The idea behind the VAR model is that variables influence each other in the system. This relationship can be tested using the Granger causality test. It tests the null hypothesis that the lag coefficients in the regression equation are zero. So, this null hypothesis will be rejected if the *p*-value obtained is less than the significance level of 0.05. Before carrying out the Granger test, we first test for stationarity of our time series. Based on the Augmented Dickey–Fuller test all four series are stationary.

The definition of causality assumes that in order to establish a causal ordering we should have some prior knowledge. As indicated by Sims (1980) and supported by Anderson and Hsiao (1982), "If a model is specified according to a set of incorrect laws, the estimation is biased, and the model may thereby become useless as a framework within which to do formal statistical tests"; thus, we assume a model without restrictions based on supposed prior knowledge. The test is based on the following OLS regression model:

$$y_i = \alpha_0 + \sum_{j=1}^{m} \alpha_j y_{i-j} + \sum_{j=1}^{m} \beta_j x_{i-j} + \varepsilon_i$$

where, α_j and β_j are the regression coefficients and ε_i is the error term. Based on the null hypothesis

$H_0 : \beta_1 = \beta_2 = \ldots = \beta_m = 0$, we say that x Granger-causes y when the null hypothesis is rejected. We use the usual F-test to determine whether there is a significant difference between the regression model above based on the null hypothesis, without the β_j terms. If the *p*-value for this test is less than the designated value, then the null hypothesis is rejected, leading to the conclusion that x Granger-causes y.

In Table 2, the rows are the response (y) and the columns are the predictor series (x). All the *p*-values are greater than 0.05 except the *p*-value = 0.021 between RELI_x and LEXP_y. So, the spirituality index Granger-causes the life experience sentiments. Meaning, the level of spirituality/religiosity determines the quality-of-life experience. This is in line with

Křeménková and Novotny (2015) who analyzed how much faith affects life meaningfulness through an existential scale (ES) questionnaire. An ES questionnaire is able to detect a subjective measure of personal meaningful existence in two dimensions: personality (sub-dimensions self-distance and self-transcendence) and existentiality (sub-dimensions freedom and responsibility). Using a post hoc Games–Howell, they realized that believers (Christians and Buddhists) scored significantly higher on personality, self-transcendence, and self-distance than atheists.

Though 0.05 is such a widely used threshold, one could argue that 0.1 is already significant, hence implying that the COVID-19 (COVI) Granger-causes life experience (LEXP), since the p-value is 0.063 between COVI_x and LEXP_y. This confirmed the disruption brought by the pandemic into the lives of many.

Table 2. Granger causality p-values.

	RELI_x	**COVI_x**	**LPURP_x**	**LEXP_x**
RELI_y	1	0.6133	0.1039	0.1843
COVI_y	0.3512	1	0.2703	0.1414
LPURP_y	0.1275	0.7354	1	0.4342
LEXP_y	0.021	0.063	0.5021	1

3.3. Marginal Contribution to Depression

$$\Delta CToD_q^{c|i} = \left(CToD_q^{c|i} - CToD_{0.5}^{c|i}\right)/CToD_{0.5}^{c|i}$$

where $CToD_{0.5}^{c|i}$ represents the normal/median state of the population conditional to variable i being at its Threshold of Depression.

As displayed in Table 3, the ToD is not the same for all our variables: $ToD_q^3 > ToD_q^4 > ToD_q^1 > ToD_q^2$. The threshold score for COVID-19 is -0.19, which is the smallest. This may give a false impression that COVID-19 had only a mild effect on the population. However, by extending the assessment to life purpose (LPURP) and life experience (LEXP) of the population involved, the higher threshold scores of these two variables reveal how severely COVID-19 impacted the population under study. Thus, the impact of the COVID-19 pandemic on the well-being of the population cannot be assessed in isolation using only the sentiment scores from COVID-19 tweets. The last column of Table 3 displays the contribution of each variable to the distress experienced by the population. LEXP and LPURP appear to be the top contributors; in other words, they seem to be a true reflection of the state of mind of the population. Besides COVID-19, variables such as unemployment, rising of cost of living, and high interest rates may have also played significant roles in driving the depression among the population. Future studies will focus on the pre-COVID-19 and post-COVID-19 periods to assess the impact of variables other than COVID-19 on LEXP and LPURP.

Table 3. Conditional Threshold of Depression.

	w_i	ToD_q^i	$CToD_q^{c\,|\,i}$	$CToD_{0.5}^{c\,|\,i}$	$\Delta CToD_q^{c\,|\,i}$
r_1	0.25	0.65	0.49	0.32	0.53
r_2	0.25	0.19	0.41	0.36	0.14
r_3	0.25	0.89	0.51	0.28	0.82
r_4	0.25	0.87	0.51	0.28	0.82

Note: $r_1 = RELI$, $r_2 = COVI$, $r_3 = LPURP$, $r_4 = LEXP$; w_i represents the weights assigned to variable r_i, ToD_q^i is the Threshold of Depression of the variable r_i, $CToD_q^{c|i}$ is the Threshold of Depression of the population conditional on the variable r_i being at its Threshold of Depression. $\Delta CToD_q^{c|i}$ is the marginal contribution to the depression of the population by the variable r_i.

3.4. Discussion

Chan et al.'s (2018) findings suggest that having a firmly held religious belief can provide a sense of increased purpose in life among those who are socially disconnected. Various lockdowns imposed by governments around the world and particularly in South Africa led to isolation and a socially disconnected society. Our study suggests that religion Granger-causes life experience, i.e., as in Chan et al. (2018), religious belief can influence our life experience. Figure 2 shows that, in terms of life purpose and life experience, many of the sentiment scores are above 0.5, indicating a population that has remained indifferent or highly positive toward life. This could have been attributed to religion, but religion sentiment scores from Figure 2 are concentrated between -0.5 and 0.5, indicating a quasi-nonaligned position toward religious belief. Maybe this level of faith is enough to explain the attitude observed toward life experience and life purpose. However, future studies in other countries may shed more light on this. Still, in Figure 2, the COVID-19 sentiment scores are concentrated between -0.2 and 0.2 suggesting that a large part of the community may have been quite indifferent toward the pandemic. Should it be as in the quote from Friedrich Nietzsche, "Those who have a 'why' to live, can bear almost any 'how'," that the community has a great sense of "'why' to live" or "life purpose" allowing them to bear almost any how? In that sense, we would have expected to observe that life purpose Granger-causes COVID-19. This quote from Friedrich Nietzsche is also supported by the Viennese psychologist Viktor Frankl in his book *Man's Search for Meaning* (1985) (Frankl 1985). We believe additional tools or methods will be needed to investigate this further.

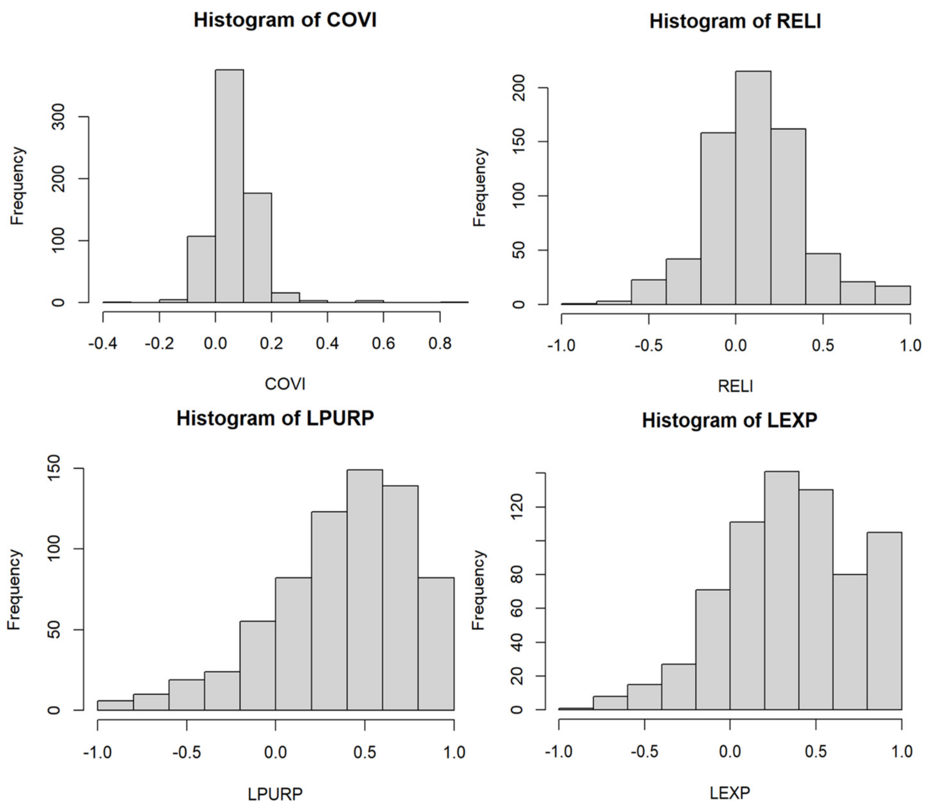

Figure 2. Histograms. Notes: The vertical axes represent the frequencies, and the horizontal axes represent the sentiment scores.

The most exciting part of this study focuses on the systemic causality, i.e., computation and analysis of the Threshold of Depression of a community given that a particular factor is at its Threshold of Depression. This risk measure was introduced in the financial system by Tobias and Brunnermeier (2016) to compute the Conditional Value-at-Risk (CoVaR), which is the VaR of the financial system given that a financial institution is at its Value-at-Risk. At the level of an individual, the risk is characterized by a high negative emotion represented by a high negative sentiment score and the Value-at-Risk is named here as the Threshold of Depression (ToD). According to Table 3, the life purpose and life experience factors have a ToD of 0.89 and 0.87, respectively, which is higher than the other two. This suggests that these two factors may be a good indicator for the psychological well-being of the population. Thus, during a crisis period in the community under study, the size of the population with sentiment scores greater than 0.89 should be closely monitored in order to provide adequate support needed by this group. This approach may be used as a first-hand risk management assessment. The central influence of life purpose and life experience is supported by their CToD values of 0.51, which is again the highest. This indicates that the community is more likely to be under distress when these factors are at their ToD, as they contribute the most (with a $\Delta CToD_q^{c|i}$ value of 0.82) to the risk of the community being in distress.

4. Conclusions

The COVID-19 pandemic has had a global impact just by looking at the number of cases and deaths associated with it. For example, as of March 2022, South Africa recorded more than 3.7 million cases and nearly 100,000 COVID-19 deaths. To cope with such a crisis, faith in a higher power is one of the mechanisms mostly used among the population. The data used in this study consist of COVID-19, religion, life experience, and life purpose tweets from users in the geographical area of South Africa during the period 11 February 2020 to 31 December 2021. The Valence Aware Dictionary and sEntiment Reasoner (VADER) were employed to compute the sentiment scores of each of these variables.

The sentiment scores for COVID-19 show some extreme spikes at the beginning of the pandemic, illustrating the confusion and high uncertainty it brought. Then, immediately after a short period, a relatively constant trend is witnessed depicting various segments of waves and implied regulations/lockdowns experienced by the population. Using the Granger causality test, we found that, at a 95% confidence level, the religious sentiment scores series Granger-causes life experience. Meaning that there is a relationship/interdependence between religion and life experience during the crisis period. This may suggest that the attitude (whether positive or negative) of the community has an impact on the life experience of its members. This is in line with Křeménková and Novotny (2015) who analyzed how much faith affects life's meaningfulness through an existential scale (ES) questionnaire. When lowering the confidence level to 90%, we found that COVID-19 Granger-causes life experience. Thus, we may postulate that the negative impact of COVID-19 is dynamically being corrected by religious practice to lower the level of depression within the community. To identify which of the four variables (RELI, COVI, LEXP, or LPURP) is likely to provide better insights into the level of depression experienced by the population during the COVID-19 pandemic period, we computed the marginal Threshold of Depression. We found that the well-being index (LEXP) seems to be a good candidate. Among the four variables, COVI has the lowest Threshold of Depression. This may indicate that the population was able to cope very well with the pandemic. As COVI Granger-causes LEXP, and they represent the lowest and the highest, respectively, in terms of the Threshold of Depression, there may be additional sources of the depression witnessed in the well-being index (LEXP). Are these sources of depression unemployment, the rising cost of living, or other economic conditions? This will be the focus of future studies in which the pre-COVID-19 and post-COVID-19 periods will be considered. We conclude this study by pointing out that the Threshold of Depression introduced here, in the framework of sentiment analysis, could be used by entrepreneurs, firms, or investors to track consumer attitudes toward particular products introduced in the market. In times of crisis, policymakers may use the threshold scale introduced here to monitor and design adequate responses to the crisis: For example, to provide activities, TV programs, and mental health checkpoints to assist the population when the majority are found to be beyond the computed threshold.

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