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WAVE 5

National Income Dynamics Study (NIDS) – Coronavirus Rapid Mobile Survey (CRAM)

The COVID-19 Pandemic, Hunger, and Depressed Mood Among South Africans

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N.i.D.S. NATIONAL INCOME DYNAMICS STUDY

CRAM CORONAVIRUS RAPID MOBILE SURVEY 2020

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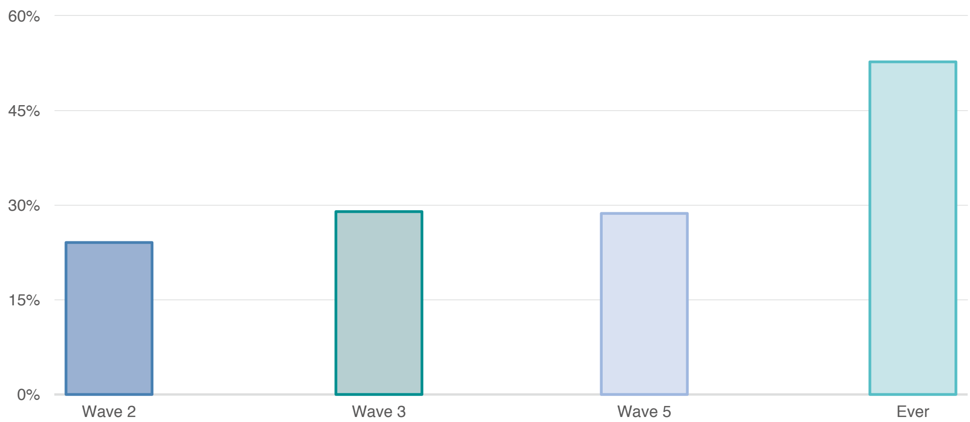
Executive summary

The COVID-19 pandemic has affected people's mental health. There are the immediate effects that include fear, anxiety, loneliness, and uncertainty about the future. But there are also secondary impacts flowing from national responses to the pandemic such as lockdowns, including school closures, halting of school feeding, as well as more distal economic impacts such as global trade slowdowns and massive increases in unemployment. We have evidence, from previous waves of NIDS-CRAM data, that rates of depressive symptoms[1] have been consistently higher than before the pandemic. The risk of screening positive for depressive symptoms had increased from 24% to 29% between waves 2 and 3 of NIDS-CRAM. In 2017, before the pandemic, this risk was 21%[2]. The risk of screening positive for "severe"[3] depressive symptoms increased from 5.2% to 7.1% between waves 2 and 3 of NIDS-CRAM.

Our findings from wave 5, collected between 6 April and 11 May 2021, indicate that the risk of screening positive for depressive symptoms has remained stable between wave 3 and 5 at around 29%. The risk of screening positive for "severe"[4] depressive symptoms, at wave 5, was 4.9%. While depressive symptoms have been and continue to be prevalent in the context of the pandemic, it is not clear what is accounting for this. Mental health is impacted by an array of factors. Many of these are internal to the individual – for instance genetics, disposition, and developmental history. But a significant amount of the variation is explained by environmental factors.[5]

Further, our analysis of all 5 panels of NIDS-CRAM data show that, while the percentage of people with high levels of depressive symptoms at each cross-section of NIDS-CRAM are in the region of 24-29%, the percentage of people who have experienced significant levels of depressive symptoms ever since the start of the pandemic, is much higher, at 52% (see *Figure 1*). This indicates that it is not the same individuals who are experiencing depression across all time points, but, rather, different individuals, moving in and out of the depressed mood category. One possible conclusion to be drawn from this phenomenon – of a changing population of people experiencing low mood – is that while some of the risk for depressive symptomatology resides within the individual, the major drivers, perhaps particularly in the pandemic, are structural and based on changing circumstances. As the pandemic drags on, and people cycle in and out of employment, and between shifting states of hunger, people move in and out of a low mood state – what we would call 'churning'.

Figure 1: Population of people affected by depressed mood at single time points compared to population ever affected by depressed mood



1 As measured by the PHQ2. From here on, where a score is mentioned, this refers to the PHQ-2 score.

2 As measured by the CES-D 10.

3 A score of 5+ on the PHQ2 which ranges from 0-6, and where a score over 3 of indicative of depressed mood.

4 A score of 5+ on the PHQ2 which ranges from 0-6, and where a score over 3 of indicative of depressed mood.

5 As well as the interplay between personal and environmental factors.

Among the environmental influences on mental health, is the ability to fulfil one's basic needs, like having stable housing, employment, and sufficient food. Hunger, in particular, is significantly associated with poor mental health, across a variety of settings. The economic downturn resulting from the pandemic has significantly impacted on economic activity, employment, and resources. The coronavirus crisis is causing disruptions in domestic food supply chains and creating strong tensions and food security risks. Given this context and our initial findings regarding churning, we explored the role of hunger in accounting for the prevalence of depressed mood and people's movement in and out of significant levels of depressed mood, over the course of the pandemic in South Africa.

At any given time point, people experiencing household hunger have higher levels of depressed mood than people not experiencing household hunger. Findings from a binary logistic regression indicated that South Africans who reported that, in the past 7 days, someone in the household had gone hungry because the household had run out of money were more likely to report a depressed mood compared to participants who did not report hunger in the past 7 days due to the household running out of money. The odds have increased over waves, from 1.51 (OR=1.52, 95% CI 1.51-1.52, p<0,001) at Wave 2, to 1.81 (OR=1.81, 95% CI 1.81-1.82, p<0,001) at Wave 3, to 1.93 at Wave 5 (OR=1.93, 95% CI 1.92-1.93, p<0,001), possibly suggesting that food insecurity is playing an increasingly important role over time.

People who are in households most affected by hunger are the most likely to experience depressed mood, but this is only true for waves 2 and 3. The likelihood of individuals screening positive for depressed mood increased significantly for those in households that reported hunger more often (every day) at wave 2 [OR=2,34, 95% CI 2,23-2,36, p<0,000] and wave 3 [OR=3,73, 95% CI 3,71-3,76, p<0,000]. However, the inverse is true for wave 5 [OR=0,900, 95% CI 0,89-0,91, p<0,000], but this is likely an artefact of the low number of responses to hunger severity items at wave 5[6]. At wave 2, 15.53% of people reporting hunger in the household also reported that they were experiencing hunger between 1 day, and every day, in the past week. In wave 3, this was 17.92, and in wave 5, 15.87%.

Respondents from households where adults are reporting hunger, but child hunger is not being reported, are at risk of low mood. However, those from households where adults and children are going hungry, are the worst off in terms of mood. We found that adults may be 'shielding' children from the effects of hunger. In between 5 and 8% of cases (varying by wave), respondents from households in which children were residing indicated that there is hunger in the household, but that children in the household are not going hungry. While there may be other explanations for this phenomenon (such as parents feeling ashamed to report that children are hungry, or simply not being aware of child hunger) we found that respondents potentially reporting 'shielding' were significantly more likely to report depressed mood at wave 2 [OR=1,25, 95% CI 1,24-1,25, p<0,000], wave 3 [OR=1,37, 95% CI 1,36-1,37, p<0,000], and wave 5 [OR=1,58, 95% CI 1,57-1,58, p<0,000]. **What is notable, however, is that depressed mood is most likely among respondents reporting that there was hunger in a household and a child was among the members going hungry.** Households with hunger among adults and children, compared to households where adults were hungry, but children were not, were more likely to explain variance in depressed mood at wave 2 [OR=1.47, 95% CI 1.47-1.47, p<0.001], and wave 5 [OR=2,70, 95% CI 2,26-2,27, p<0.001].

Based on our findings, it is apparent that government must prioritise immediate relief from the acute drivers of psychological distress. In South Africa, these factors include job loss and unemployment, food insecurity, and associated hunger. Job creation, food support, and social safety nets such as grants could alleviate the acute distress of many South African households.

6 While the overall proportion of responses to the hunger severity question are the same at waves 2 and 5, there are differences in the proportions across response options (days going to be hungry) which make the wave 5 data of less utility than the wave 2 data. For instance, at wave 2, there are 3.05% of responses in the "almost every day category", whereas, at wave 5, there are much lower proportions in the 'every day' levels (1.3%). This is affecting the directionality of the relationship.

Note on measures and data collection

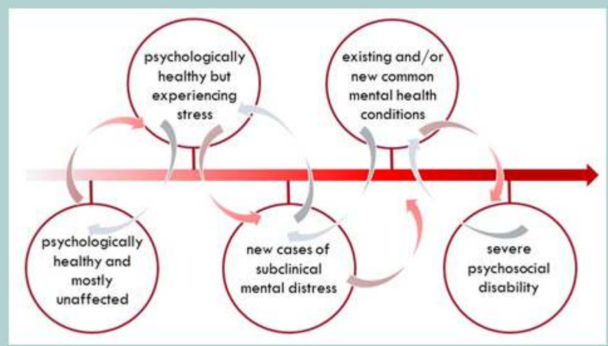
Depressed mood data were only collected during **waves 2, 3 and 5** of NIDS-CRAM. As such, we are unable to report on mental health during waves 1 and 4.

Data on depressed mood collected during waves 2, 3 and 5 used the **Patient Health Questionnaire-2 (PHQ-2)**. The PHQ-2 enquires about the frequency of depressed mood and anhedonia (loss of enjoyment) over the past two weeks. The PHQ-2 includes the first two items of the PHQ-9, a longer measure of mental health. The purpose of the PHQ-2 is to screen for depression in a stepped system of screening, where people who screen positive on the 2-item measure are further evaluated with the PHQ-9 to determine whether they meet criteria for a probable depressive disorder. The PHQ-2 is scored from 0 to 3 on each of its 2 items, providing a combined score on a scale of 0 to 6, with scores of 3 and above indicating depressed mood. The comparator reference in past NIDS-CRAM analyses reporting depressed mood among South Africans is based on data collected using the **Center for Epidemiological Studies-Depression measure (CES-D-10)**. It is a 10-item Likert scale questionnaire assessing depressive symptoms in the past week. It includes three items on depressed affect, five items on somatic symptoms, and two on positive affect. Options for each item range from "rarely or none of the time" (score of 0) to "all of the time".

Background

What do we mean by mental health and depressed mood?

Poor mental health and mental health conditions are different things. Mental health is not an either/or phenomena but rather falls on a continuum. At the one end is where our mood is upbeat and stable most of the time, our affect (the emotions we show) is positive, and we are able to go about the tasks of daily life without our feelings and thoughts getting in the way. At the other end of the spectrum, we feel poorly, our mood fluctuates (frantic or subdued), and is at times unstable. Our emotional world can be tumultuous or painfully flat, and for many the basic tasks of daily life are extremely difficult if not impossible. Most people may at times move along this spectrum of thought and feeling, but for the most part will not reside at either extreme. Having a mental health condition means inhabiting the extreme end of the continuum, for a prolonged period of time. A mental health condition requires diagnosis and treatment, and – although the range of mental health conditions can range from non-severe to serious – they are by definition more extreme than the sub-clinical fluctuation in mood which is better described as poor mental health. Somebody reporting that they feel sad often on a survey cannot be described as depressed in the same way that a person with clinically diagnosed depression would be. If they were formally assessed, they may well turn out to be depressed, but for the purposes of reporting such responses – the left half of this continuum, but not necessarily the extreme end – we describe people as having depressed mood, rather than depression.



On this continuum of affectedness, we see people at the one end are those who are psychologically healthy and mostly unaffected. Further along, are those who are otherwise psychologically healthy, but who are encountering stress related to the consequences of COVID and/or lockdowns, and reporting depressed mood. But, for this group, most might be quite resilient. Yet, if the acute distress for this group begins to become more chronic many will now begin to experience clinically significant levels of mental distress. There will also be a group of people who had common mental health conditions before the pandemic, and for whom the effects of the pandemic and/or lockdowns might be most acutely felt and who need additional support and those who have become newly affected by a diagnosable common mental health condition due to the consequences of COVID and/or lockdowns. Finally, there are people with severe psychosocial disability who require significant additional support to get through this time.

Since 31 December 2019, when the World Health Organization officially announced the first case of a novel Coronavirus, the world has experienced an unprecedented global pandemic, with over 181 million infections, 3,93 million deaths (as of 28 June 2021), and a resulting series of country lockdowns[7] and responses to multiple spikes in infection rates, in virtually every country of the world. The pandemic has had devastating impacts in all countries, with high mortality rates particularly among the aged and those with co-morbid conditions. As concerning, however, are the effects of containment measures necessary to slow the virus' spread. There has been a global upsurge in job loss [1], hunger [2], isolation [3], and domestic violence [4], to name a few. Concomitant with, and partly resultant from, these changes, has been a deterioration of people's mental health.

7 Due to the COVID-19 pandemic, containment measures (called lockdowns) have been implemented around the world. These measures encompass stay-at-home orders, curfews, quarantines, and similar societal restrictions. They aim to reduce the spread of the virus which causes COVID-19.

In general (and in periods not marked by a pandemic), people's mental health – that is, their psychological wellbeing, sense of happiness or sadness, and presence or absence of mental health conditions – is impacted by a huge array of factors. Many of these are internal to the individual – for instance genetics, disposition, and developmental history [5, 6]. But a significant amount of the variation in how good or poor people's mental health is, is explained by their circumstances [7-10]. The environments in which we live are either enabling ones, that scaffold and facilitate our lives and development on the one end of the spectrum, while on the other they might be contexts full of barriers that limit our people's potential [7-11]. Among these environmental, social, community, and interpersonal influences on mental health, is the ability to fulfil one's basic needs, like having stable housing and enough food [12-15]. While it is unclear the extent to which the pandemic may impact upon the internal drivers of mental health problems, what is apparent is the direct and devastating effect which the COVID-19 pandemic has had on the external drivers of distress.

Immediate Effects of Covid-19 on mental health

During a crisis such as the COVID-19 pandemic, people are affected in a variety of ways. Individuals may feel fear and anxiety about getting sick or losing a loved one, and uncertainty about the future; when will things go back to normal? [16]. Those who are unfortunate and lose loved ones will also experience loss and grief. Some people are at greater risk of feeling significant stress during a pandemic, including people who are at higher risk for severe illness from COVID-19 (for example, older people and people with underlying physical health conditions), children and adolescents, essential workers, and people who have existing mental health conditions [16].

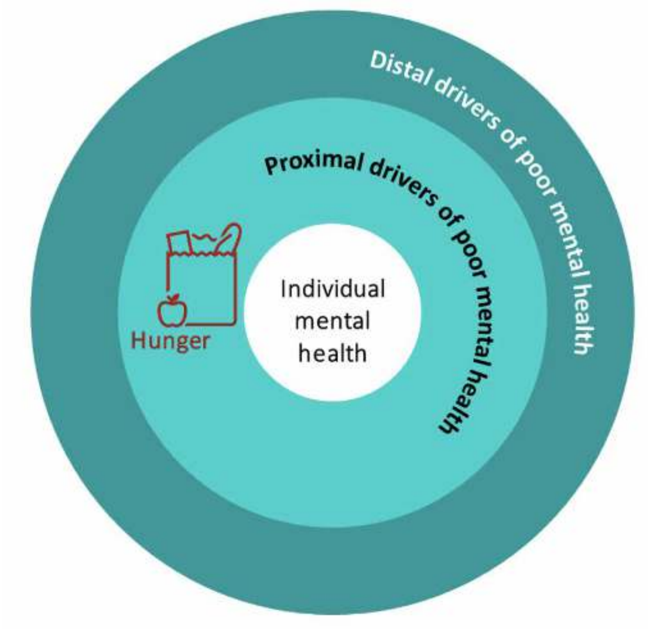
Effects secondary to lockdown

To curb the spread of the disease, measures such as countrywide lockdown, physical distancing, and quarantine have been implemented almost worldwide [17]. Many of the consequences of lockdown and social and physical distancing measures are key risk factors for mental health issues, including suicide and self-harm, alcohol and substance misuse, gambling, domestic and child abuse, and psychosocial risks (such as parenting stress, social disconnection, financial stress, hunger, unemployment, and homelessness) [18].

The fallout of the economic downturn associated with the pandemic, particularly, on mental health is likely to be profound [18]. In many countries which implemented lockdowns, particularly those which are low- and middle-income, the economic activities and daily earning of many people came to a halt [17]. In low- and middle-income countries like South Africa, where a significant proportion of the population works in the informal sector, such measures spelt a looming dual crisis of disease- and poverty-related strife [17]. More than 60% of the world's employed population, approximately 2 billion people, work in the informal economy [19]. In South Africa, the informal economy represents approximately 30-34% of the workforce though this estimate does not necessarily include domestic workers [19-21]. As noted by Bhatia and Kamble [17], the economic effects of lockdowns disproportionately affect the poor.

According to the International Labor Organization, in 2020, 8.8 per cent of global working hours were lost, equivalent to 255 million full-time jobs [1]. Perhaps unsurprisingly, then, comes the World Food Program's caution that COVID-19 has increased the number of people facing acute food insecurity in 2020-2021, with 272 million people currently, or at risk of becoming, acutely food-insecure in the countries where it operates [22]. As the World Bank notes, the coronavirus crisis is causing disruptions in domestic food supply chains and creating strong tensions and food security risks in many countries [23].

Figure 2: Proximal and distal drivers of depressed mood in the environment



As represented in *Figure 2*, hunger is a proximal environmental driver of poor mental health. It is something close to the individual which, on the basis of past evidence, we can anticipate will play a significant role in people's mental health. It is also something which comes about often in response to the kinds of crises of unemployment and economic downturn (more distal factors) associated with the COVID-19 pandemic.

South Africa is a middle-income country characterized by poverty and extreme inequality, high burdens of violence, communicable and non-communicable diseases, factors which place much of the population at ongoing risk of anxiety, depression, and traumatic stress [24-27]. Prevalence estimates of mental health conditions among South African adults before COVID suggest that up to 15% will experience anxiety disorders and 9.8% mood disorders in their lifetime8 [25]. In this context, South Africa has been ill-prepared for the strains associated with a crisis, particularly one of the magnitude of the COVID-19 pandemic. The present paper explores the state of South Africans' mental health as documented over 3 waves of mental health data collection spanning the year and a half, with a focus on understanding the role which hunger – one switch on a complicated dial of determining factors influenced by the pandemic – is playing in people's mood.

8 Prevalence estimates in the country vary widely depending on the measures used, the models used to produce estimates, as well as the characteristics of the population surveyed. Representative and population-level surveys are lacking, but smaller epidemiological studies with subpopulations like pregnant women and people seeking HIV testing and counselling, show higher rates of common mental disorders including depression (39% [28] and 14.2 % [26] respectively). 28. Hartley M, Tomlinson M, Greco E, Comulada WS, Stewart J, Le Roux I, et al. Depressed mood in pregnancy: prevalence and correlates in two Cape Town peri-urban settlements. Reproductive health. 2011;8(1):1-7. 26. Kagee A, Saal W, De Villiers L, Sefatsa M, Bantjes J. The prevalence of common mental disorders among South Africans seeking HIV testing. AIDS and Behavior. 2017;21(6):1511-7.

Methods

Key Findings from prior waves of NIDS-CRAM

Wave 2: Oyenubi and Kollamparambil (2020)

The authors compared the prevalence of depressive symptoms in 2017 (before COVID-19) and 2020. Depressive symptoms had increased significantly in 2020 relative to 2017. Moreover, the likelihood of having depressive symptoms changed across key demographic variables. While the gap in depressive symptoms across some categories (like gender) had reduced, depressive symptoms – overall – increased. Job loss was an important correlate of depressive symptoms.

Wave 3: Oyenubi and Kollamparambil (2021)

The authors showed that the distribution and the risk of screening positive for depression had increased in wave 3 relative to wave 2. The risk of screening positive had increased significantly for Black Africans, only. The protective effect of social security grants and household size had dissipated in wave 3 relative to wave 2. People in formal employment were protected against depressive symptoms compared to others. Hunger and hunger severity were correlated with the risk of screening positive for depressive symptoms, and the relationship had strengthened in wave 3 compared to wave 2. There was a decline in individuals reporting risk of infection, which mitigated the increased depression scores between the two waves.

Wave 3: Nwosu (2021)

The author we showed that there was positive association between spending more hours on childcare and worse mental health for caregivers, and the association was stronger for men. Furthermore, the childcare-mental health relationship was significantly mediated by childcare responsibilities limiting the ability of caregivers to work as well as preventing caregivers from searching for jobs.

Wave 3: Benhura and Magejo (2021)

The authors showed that the likelihood of experiencing depressive symptoms increased for all workers between June and October of 2020. They reported no statistically significant differences between informal and formal workers' mental health over this period. Additional results showed that workers living in urban areas and households suffering from hunger had a higher risk of experiencing depressive symptoms.

Wave 3: Van der Berg, Patel, and Bridgman (2021)

The authors explored hunger across the first 3 waves of NIDS-CRAM. They noted that while the first wave data provided strong evidence of drastic increases in household and child hunger during the initial period of the Coronavirus pandemic, the second wave of NIDS-CRAM showed improvement, although hunger and food insecurity remained high. They went on to show that in wave 3, indicators of hunger and food insecurity had again worsened after the improvement in Wave 2, possibly due to phasing out of the top-ups to some of the social grants following the strict lockdown of early 2020.

This study makes use of the third wave of the NIDS-CRAM survey data. Data collection for the wave 1 took place between 7 May and 27 June 2020 (i.e., stages 3 and 4 of the national lockdown), wave 2 took place between 13 July and 13 August 2020 (i.e., 'advanced' stage 3 of the lockdown), wave 3 took place between 2 November and 13 December 2020, and wave 5 took place between 6 April and 11 May 2021. Due to attrition in waves 2 and 3, there was also a refresher sample added to wave 3 which meant a total of 1 084 participants were added to wave 3, to make the sample more representative of the population. This study analysis focused specifically on waves 2, 3 and 5. Analysis were done on weighted data as far as possible. The following weight variables were used: wave 2 = w2_nc_pweight_s; wave 3=w3_nc_pweight_s; wave 5= w3_nc_pweight_s, and where all three waves were included in the analysis, we used=w5_nc_bp_pweight_s.

All analyses were completed in STATA version 17.0. Following descriptive statistics describing the prevalence of variables of interest, chi-square analysis was used to explore the association between independent variables of interest and depressed mood. Where significant association were found, binary logistic regression was used to explore a potential significant relationship between the independent variable and depressed mood. Significant relationships found in the binary logistic regression analysis were further explored using multiple logistic regression to determine the relationship between the independent variables and depressed mood while controlling for key confounding variables. Significance was set at $p<0.05$.

Findings

Prevalence and severity of depressed mood

Based on our analyses of depressed mood prevalence (frequencies of PHQ-2 scores in the range 0-2, and 3+), we found that the risk of screening positive for depression has increased from 24% to 29% of the population between waves 2 and 3 of NIDS-CRAM, and remained stable in wave 5, at 29%. We also examined the prevalence of 'severe' depressed mood – the frequency of scores on the PHQ2 falling into the 5+ category, on a scale of 0-6, versus scores falling between 0-4. We found that the risk of screening positive for 'severe' depressed mood increased from 5% to 7% of the sample between waves 2 and 3 of NIDS-CRAM, and was 5% in wave 5. Prevalence statistics are summarised in *Table 1*.

Table 1: Prevalence of depressed mood, 'severe' depressed mood, across waves of NIDS-CRAM with mental health data

	Depressed mood	'Severe' depressed mood
Wave 2	24%	5%
Wave 3	29%	7%
Wave 5	29%	5%

Note. Weighted data was used in the analysis.

Movement in and out of depressed mood

We then compared the point prevalence of depressed mood at each wave of NIDS-CRAM, with the prevalence of unique cases of depressed mood across all three time points with mood data. We find that while the rates of depressed mood (3+ on the PHQ2) was in the range of 24% - 29% at any single wave, the proportion of people who had reported depressed mood ever – at either wave 2, or 3 or 5 – was much higher – over half of the sample (52.07%).

As such, it is different individuals who are occupying the depressed mood group at least some of the time. This is opposed to what one might expect with a clinical population of people with depressed mood, where it would be the same 15% or so of individuals experiencing chronic distress. *Table 2* shows how the proportion of unique cases of depressed mood varies over time.

Figure 3: Population of people affected by depressed mood at single time points compared to population ever affected by depressed mood

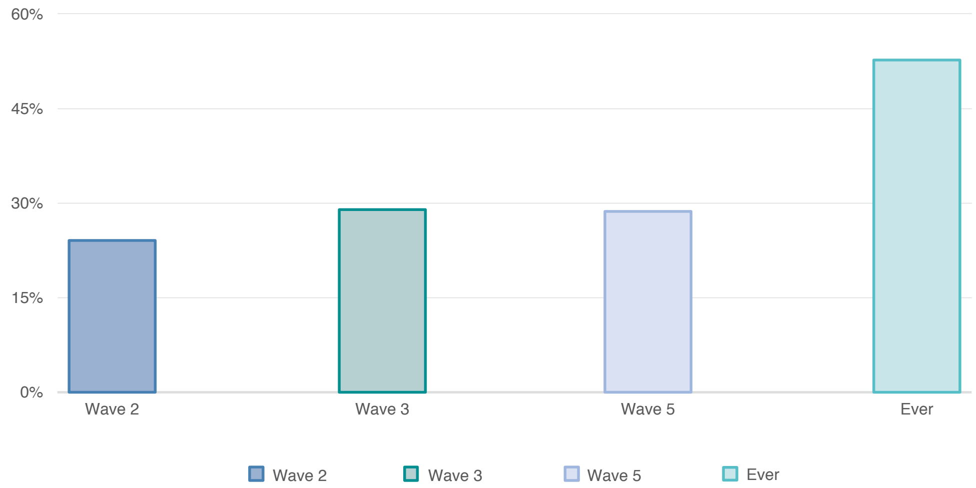


Table 2: Proportion of people reporting depressed mood at wave 2 only, wave 3 only, wave 5 only, and all three waves

Time point/s	Percentage
*Wave 2 only depressed mood	14.9
*Wave 3 only depressed mood	10.2
*Wave 2 only depressed mood	11,3
All three waves depressed mood	6.61

Factors associated with depressed mood cross-sectionally

While inferential statistics have been conducted on the mental health data in line with specific interest areas in past waves (see Box 2: Key Findings from Prior Waves of NIDS-CRAM) we conducted a series of Chi Square Tests to inform further analyses regarding demographic variables significantly associated with depressed mood cross-sectionally at waves 2, 3 and 5. We found no significant association between **age**[9] and depressed mood at wave 2 [chi-square (6) = 10,6; p<0.100], wave 3 [chi-square (6) = 10,7; p<0.097] or wave 5 [chi-square (6) = 3.14; p<0.791]. We also found no significant association between **gender** and depressed mood at wave 2 [chi-square (1) = 2,99; p<0.084] or wave 5 [chi-square (1) = 0,62; p<0.429]. We did, however, find a significant association between **gender** and depressed mood at **wave 3** [chi-square (1) = 5,83; p<0.016], with males being more likely to report depressed mood than females (OR=1.05, 95% CI 1.05-1.05, p<0.000).

We also found that **employment type**[10] among individuals aged 15 years or older were significantly associated with depressed mood at wave 2 [chi-square (3) = 20,6; p<0.000] and wave 3 [chi-square (3) = 13,1; p<0.004] but not wave 5 [chi-square (3) = 2,5; p<0.475]. A binary logistic regression (see below, *Table 3*) revealed that those respondents who reported having a regular job during wave 2 were 1.4 times less likely to report a depressed mood compared to those participants who did not (OR=1.43, 95% CI 1.425-1.429, p<0.000).

9 A Chi Square test was used given the categorical nature of the age variable.

10 The response options included “regular job”, “casual work”, “self-employed”, and “I run a business”.

Table 3: Logistic regression exploring relationship between employment type and depressed mood at wave 2

	Odds ratio	Standard Error	Z	P value	95% CI
Employment type (Regular job)	1.43	0.00098	522.51	0.000	1.43-1.43
Constant	0.19	0.00024	-1299.37	0.000	0.19-0.19

Note: R^2 = 0.0150

Similarly, those participants who reported having a regular job during wave 3 were 1.3 times less likely to report depressed mood compared to those participants who did not (OR=1.34, 95% CI 1.34-1.35, p<0.000) (see *Table 4*, below).

Table 4: Logistic regression exploring relationship between employment type and depressed mood at wave 3

	Odds ratio	Standard Error	Z	P value	95% CI
Employment type (Regular job)	1.34	0.00077	512.57	0.000	1.34-1.36
Constant	0.25	0.00029	-1198.03	0.000	0.25-0.25

Note: R^2 = 0.0119

Being unemployed was not significantly associated, cross-sectionally, with depressed mood in wave 2, 3, or 5. However, longitudinally, new unemployment (i.e., job loss) was significantly associated with new onset depressed mood (see more below).

In an additional series of Chi Square tests, we found a significant association between **changes in household income in the past 4 weeks** and depressed mood at wave 2 [chi-square (2) = 10,7; p<0.005], and wave 5[chi-square (2) = 16,6; p<0.000] but not wave 3 [chi-square (2) = 0,634; p<0.728]. A logistic regression showed that decreased household income was associated with depressed mood at wave 2 (OR=1.31, 95% CI 1.31-1.31, p<0.000), wave 3 (OR=1.10, 95% CI 1.10-1.10, p<0.000), and wave 5 (OR=1.25, 95% CI 1.25-1.25, p<0.000) (see *Tables 5-7*, below).

Table 5: Logistic regression exploring relationship between changes in household income and depressed mood at wave 2

	Odds ratio	Standard Error	Z	P value	95% CI
Increased	0.83	0.00087	-178.80	0.000	0.83-0.83
Decreased	1.31	0.00136	257.56	0.000	1.31-1.31
Constant	0.30	0.00016	-2152.78	0.000	0.30-0.30

Note: R^2 = 0.0038

Table 6: Logistic regression exploring relationship between changes in household income and depressed mood at wave 3

	Odds ratio	Standard Error	z	P value	95% CI
Increased	0.91	0.00137	-63.92	0.000	0.91-0.92
Decreased	1.07	0.00086	82.57	0.000	1.07-1.07
Constant	0.41	0.00021	-1739.27	0.000	0.41-0.41

Note: R^2 = 0.0003

Table 7: Logistic regression exploring relationship between changes in household income and depressed mood at wave 5

	Odds ratio	Standard Error	z	P value	95% CI
Increased	1.04	0.00108	37.21	0.000	1.04-1.04
Decreased	1.25	0.00132	213.80	0.000	1.25-1.26
Constant	0.39	0.00018	-2068.01	0.000	0.39-0.39

Note: $R^2 = 0.0011$

Relationships between hunger and depressed mood

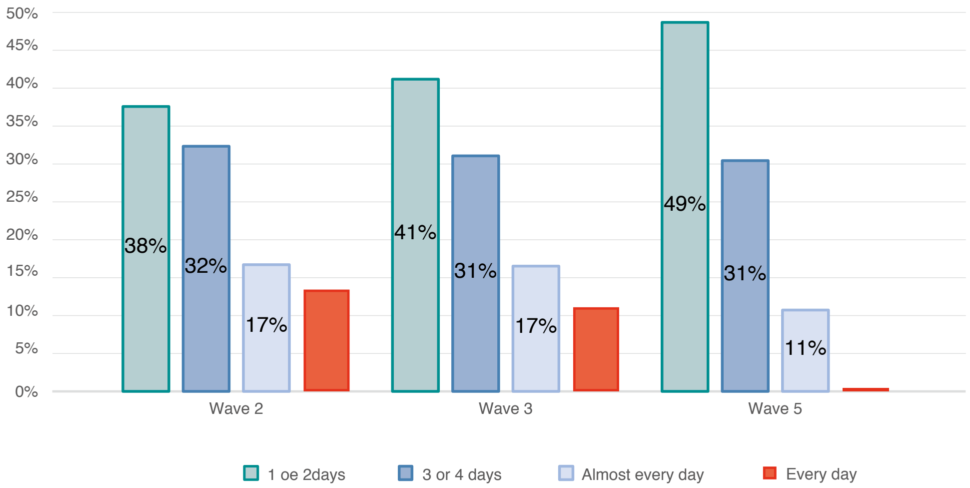
When respondents recorded that they were living in a household where people were going hungry, hunger severity items were administered to them. The hunger severity question was:

How often did they go hungry?

1. Never 1
2. 1 or 2 days 2
3. 3 or 4 days 3
4. Almost every day 4
5. Every day 5

The distribution of responses over waves 2, 3 and 5 for these items are presented in *Figure 4*.

Figure 4: Prevalence of different degrees of hunger severity over time



Findings from a binary logistic regression examining the relationship between household hunger and depressed mood showed that those participants who reported that in the past 7 days someone in the household has gone hungry because the household has run out of money were **more likely** to report a depressed mood compared to this participants who did not report hunger in the past 7 days due to the household running out of money, and the odds increased from 1.52 at wave 2 (OR=1.52, 95% CI 1.51-1.52, p<0.000), to 1.81 at wave 3 (OR=1.81, 95% CI 1.81-1.82, p<0.000), to 1.93 at wave 5 (OR=1.93, 95% CI 1.92-1.93, p<0.000) (see *Table 8-10*, below).

Table 8: Logistic regression exploring relationship between hunger and depressed mood at wave 2

	Odds ratio	Standard Error	z	P value	95% CI
Hunger	1.52	0.00151	416.22	0.000	1.51-1.52
Constant	0.30	0.00012	-2820.17	0.000	0.30-0.30

Note: $R^2 = 0.0042$

Table 9: Logistic regression exploring relationship between hunger and depressed mood at wave 3

	Odds ratio	Standard Error	Z	P value	95% CI
Hunger	1.81	0.00162	666.17	0.000	1.81-1.82
Constant	0.37	0.00015	-2381.47	0.000	0.37-0.37

Note: $R^2 = 0.0099$

Table 10: Logistic regression exploring relationship between hunger and depressed mood at wave 5

	Odds ratio	Standard Error	z	P value	95% CI
Increased	1.93	0.00181	698.93	0.000	1.93-1.93
Constant	0.36	0.00015	-2490.76	0.000	0.36-0.36

Note: $R^2 = 0.0109$

A multiple logistic regression between hunger and depressed mood while controlling for gender, race, household income and a grant[11] showed that hunger explained a significant amount of variance at wave 2 and 3 while controlling for these factors but not at wave 5 (see *Tables 11-13*).

Table 11: Multinomial logistic regression exploring hunger and mental health, controlling for relevant demographic variables, at wave 2

	Coefficient	Standard Error	z	P value	95% CI
Hunger	0.33	0.10778	3.04	0.002	0.12-0.54
Race	0.39	0.28177	1.40	0.161	-0.16-0.95
Lost income	0.10	0.13289	0.73	0.465	-.16-0.38
Household income	-0.04	0.03512	-1.19	0.233	-0.11-0.03
Constant	-2.50	0.60183	-4.12	0.000	-3.66-1.30

Note: $R^2 = 0.0275$

11 The results presented here are for households receiving the child support grant. We also ran the model with households which had received any grant, and it did not change the overall finding.

Table 12: Multinomial logistic regression exploring hunger and mental health, controlling for relevant demographic variables, at wave 3

	Coefficient	Standard Error	Z	P value	95% CI
Hunger	0.30	0.10218	2.89	0.004	0.09-0.50
Race	0.16	0.27246	0.58	0.559	-0.37-0.69
Lost income	0.21	0.16341	1.31	0.192	-0.11-0.53
Household income	-0.76	0.03894	-1.94	0.052	-0.15-0.00
Constant	-1.86	0.58858	-3.17	0.002	-3.02- -0.71

Note: R^2 = 0.0233

Table 13: Multinomial logistic regression exploring hunger and mental health, controlling for relevant demographic variables, at wave 5

	Coefficient	Standard Error	Z	P value	95% CI
Hunger	-0.01	0.11698	-0.04	0.964	-0.23-0.22
Race	0.90	0.53776	1.68	0.094	-0.15-1.96
Lost income	0.06	0.15132	-0.37	0.711	-0.35-0.24
Household income	0.07	0.05506	-1.34	0.181	-0.18-0.3
Constant	0.89	0.74736	-1.19	0.233	-2.36-0.57

Note: R^2 = 0.0178

We also conducted a logistic regression to explore the relationship between hunger severity and depressed mood. Findings from the logistic regression showed a significantly increased likelihood of screening positive for depressed mood for households that report hunger more often (every day) at wave 2 [OR=2,34, 95% CI 2,23-2,36, p<0.001] and wave 3 [OR=3,73, 95% CI 3,71-3,76, p<0.001], but the inverse is true for wave 5 [OR=0,900, 95% CI 0,89-0,91, p<0.001].

We further explored the inverse relationship between hunger severity and depressed mood at wave 5. In a Chi Square test on the wave 5 mental health and hunger severity data, we see that, if we compare the unweighted data for participants based on hunger severity compared by depressed mood at wave 5, there is no significant difference between hunger severity scores for those participants who reported depressed mood compare to those who did not report depressed mood [chi-square (3)=2,93, p<0,402]. It is likely that the relatively small sample size for the more extreme ends of hunger severity explain this finding. Indeed, only 16% of participants responded to the hunger severity items in the weighted sample at wave 5.

Rates of adult hunger and child hunger

In past NIDS-CRAM analyses [29] researchers have reported that there are higher rates of household hunger reported than there are of child hunger. To explore this phenomenon in the wave 5 data, we produced **weighted** prevalence estimates cases where respondents answered yes to household hunger, but no to a child being hungry. Approximately 8% of participants conformed to this pattern in wave 2, while this proportion decreased in wave 3 (to approximately 7%) and 5 (to approximately 5%). It is important to note that an isolated database was created for each wave separately using section E and F of the data collection questionnaire so that the dataset used for each analysis included only those households that reported having a child in the household.

What is notable is that depressed mood was most likely among respondents reporting that there was hunger in a household and a child was among the members going hungry. Households with hunger among adults and children, compared to households where adults were hungry, but children were not, were more likely to explain variance in depressed mood at wave 2 [OR=1.47, 95% CI 1.47-1.47, p<0.001], and wave 5 [OR=2,70, 95% CI 2,26-2,27, p<0.001] (see *Tables 14-16*).

Table 14: Logistic regression exploring the relationship between households with hunger, with and without child hunger, at wave 2

	Odds ratio	Standard Error	Z	P value	95% CI
Household hunger and child hunger	1.47	0.00203	278.29	0.000	1.47-1.47
Household hunger and no child hunger ('Shielding')	1.34	0.00220	175.55	0.000	1.33-1.34
Constant	028	0.00014	-2429.91	0.000	0.28-0.28

Note: R^2 = 0.0033

Table 15: Logistic regression exploring the relationship between households with hunger, with and without child hunger, at wave 3

	Odds ratio	Standard Error	Z	P value	95% CI
Household hunger and child hunger	1.64	0.25	3.22	0.001	1.21-2.22
Household hunger and no child hunger ('Shielding')	1.31	0.31	1.24	0.216	0.85-2.03

Note: R^2 = 0.0062

Table 16: Logistic regression exploring the relationship between households with hunger, with and without child hunger, at wave 5

	Odds ratio	Standard Error	Z	P value	95% CI
Household hunger and child hunger	2.27	0.00277	671.16	0.000	2.26-2.27
Household hunger and no child hunger ('Shielding')	1.80	0.00354	294.47	0.000	1.78-1.80
Constant	0.35	0.00018	-1994.78	0.000	0.35-0.35

Note: R^2 = 0.0171

Longitudinal drivers of change in mood

Given our finding that people are moving in and out of a state of depressed mood (that there is a 'churning' population of people experiencing depressed mood), we explored the drivers of mood change. For this purpose, we examined mood change between depressed mood score and waves 3 and 5, and then explored intervening variables at wave 4 and 5, to see what might cause a move from no depressed mood, to depressed mood.

One fifth (23.3%) of participants with no missing data at either wave 3 or wave 5, experienced change in their mood between wave 3 and 5, moving either up – from not having depressed mood (a score of 0-2) to having depressed mood (a score of 3+) or vice versa.

We examined whether losing a job between time 4 and time 5 explain variance in depression change score at time 5. A logistic regression analysis demonstrated that participants who had lost their job between wave 4 and 5 were not more likely to experience a change in scores of depressed mood between wave 3 and 5 (a move from not depressed – a score of 0-2, to depressed mood – a score of 3+) (OR=1,09, 95% CI 0,78-1,28, p<0.51). A multiple logistic regression with job change and hunger inputted as independent variables together showed that losing a job explained more variance in depressed mood than hunger (OR=1,27, 95% CI 1,27-1,28, p<0.001), but hunger remained significant in the model (see *Tables 17-18*).

Table 17: Logistic regression exploring the relationship between job loss and depressed mood at wave 5

	Odds ratio	Standard Error	Z	P value	95% CI
Job change	1.09	0.18799	0.51	0.611	0.78-1.53
Constant	0.30	0.01108	-32.66	0.000	0.28-0.33

Note: R^2 = 0.0001

Table 18: Logistic regression exploring the relationship between job loss and depressed mood, controlling for hunger, at wave 5

	Odds ratio	Standard Error	Z	P value	95% CI
Job change	0.17	0.00196	88.92	0.000	0.17-0.18
Hunger	0.07	0.00109	59.50	0.000	0.06-0.07
Constant	-1.21	0.00044	-2713.99	0.000	-1.21- -1.20

Note: R^2 = 0.0003

Discussion

We found that, among a broadly representative sample of South Africans, **depressed mood continues to be prevalent**, a year and a half into the pandemic, and just over a year after South Africa implemented its first lockdown. This finding aligns with international literature which has shown that the COVID-19 pandemic has resulted in increased prevalence of depression, anxiety, distress, and insomnia [30]. Further, such findings have historical precedent, in that the prevalence of mental health problems, such as common mental disorders, substance-related disorders, and suicidal behavior, tend to be higher during a period of economic recession, such as that associated with the current pandemic [31]. However, the rates of depressed mood in South Africa (24-29%) are somewhat lower than recent international prevalence estimates published by Wu et al. [30][12], the overall pooled prevalence of depression in their analysis was 31.4%, and distress (broadly framed), 41.1%, although the majority of the included studies hailed from China, and so findings must be compared with South African findings with caution.

Notably, our findings show that – rather than being a unique group of chronically depressed individuals inhabiting the low mood group over waves – people are moving in and out of a low mood state. This 'churning' points to the important role of environmental determinants of mood in driving population-level mental health epidemiology. In line with this, we found that a range of environmental variables, such **as employment type, unemployment, loss of household income, and hunger** are significantly associated with depressed mood. These associations hold up in longitudinal analyses, where, for instance, losing a job between time 4 and time 5 explains variance

12 Their systematic review and meta-analysis included studies from China, as well as other locations. However, 62 of 66 included studies were for the Chinese population, with another one each from Iran, Jordan, Singapore, and India.

in depression change score (a change from no depressed mood, to depressed mood).

The association between employment type (i.e., full-time, part-time, temporary, and so forth) and mental health is well documented. It is thought that the precariousness of employment and income associated with categories of work outside full-time formal employment have deleterious effects on mental health [32]. However, generally, and in South Africa in particular, bidirectional relationships between socioeconomic and employment status, and mental health, have been noted. On the one hand, social causation [33] describes the phenomenon wherein adverse social and economic conditions associated with poverty, such as financial stress, increased adverse life events such as negative income shocks, food insecurity, and so forth, increase risk for mental health conditions. On the other hand, social selection or social drift describes how people living with mental health conditions may 'drift' into poverty due to loss of functioning, disability, reduced economic productivity, and other factors associated with their condition [33].

Lund and Cois (34) have shown that, instead of being mutually exclusive, competing explanations for the association between poverty and its correlates, and poor mental health, both are true. In their study, poverty predicted worse depression, and depression predicted worse poverty, over 3 waves of data [34].

Given the duration of time covered by the NIDS-CRAM study and the unique circumstances of the pandemic it would be unwise to try and draw conclusions about which (if not both) of these dynamics is playing out in South Africa at the moment. As such, we set out to explore a more acute driver of low mood: new onset unemployment. New onset unemployment has been found to predict acute and chronic mental health problems, although, the literature suggests that mental health outcomes following job loss are heterogeneous, and intermediary factors play a role [35, 36].

As such, it is not unsurprising that, while we found that employment status was not significantly associated with mood cross-sectionally, becoming newly unemployed (losing a job) was significantly associated with moving from no depressed mood, to experiencing depressed mood. NIDS-CRAM analyses from as early as June last year began to document that impact of the pandemic on employment, indicating that – at that stage – about three million South Africans lost their jobs as a result of the Covid-19 pandemic and subsequent lockdown [37]. Internationally, the pandemic has resulted in widespread job loss [38], with women and those employed in the informal sector most affected [37, 39]. In one study, for instance, women were 24% more likely to permanently lose their job than men [40]. The economic fallout of the COVID-19 pandemic, and resultant job losses, has significantly increased rates of mental distress [41].

Loss of household income – often secondary to job loss – has? a wide range of effects on individuals and families which are all associated with mental health problems. Where unemployment may have psychological consequences for the individual which have to do with feeling demotivated, hopeless, angry or a sense of loss related to the termination of employment, it is through loss of income that unemployment affects the household. Loss of income has been widespread in the context of the pandemic [42, 43].

While job type, job loss and income loss are associated with depressed mood, as outlined in the background to this paper, our particular interest lay in examining a proximal risk on the causal chain from environmental circumstances, to mental health: hunger.

We found that, at any given time point, people experiencing household hunger have higher levels of depressed mood than people not experiencing hunger. We also found that the role of hunger in depressed mood seems to be increasing over time, which may suggest that hunger is playing an increasingly important role in determining mental health over time. Further, people who are most hungry are the most likely to experience depressed mood.

The link between hunger and mental health conditions is well-established; both food insecurity and hunger are associated with depression [15, 44, 45], anxiety [45, 46], and suicidal ideation and attempts [44, 47].

Furthermore, there is existing evidence which points to the role of hunger in South African's vulnerability to depressed mood. A recent editorial for SAMJ [48], for instance, noted that the recent Maternal and Child Health (MATCH) survey [49] showed that new and prospective South African mothers who reported going to bed hungry for three or more nights in the week were five times more likely to say that they felt hopeless, down or depressed "most days" compared to those not experiencing hunger (36% compared to 8%).

The vulnerability of women – as caregivers – to hunger in the context of the pandemic leads us to a particularly interesting finding regarding child and adult hunger, which requires some (cautious) interpretation. We found that between 5% and 8% (depending on wave) of respondents with children, who are reporting hunger in the household, are reporting that no children are going hungry. This group is at risk of low mood. One possible explanation for this phenomenon of reporting household hunger but not reporting child hunger, is that adults in the household are 'shielding' children from hunger, that is, they are ensuring that that food, which is available, is being eaten by children in the household, rather than adults. This phenomenon would partly explain why these individuals are more at risk of depressed mood than other adults, as they are bearing the brunt of the effects of food insecurity in the home. However, it is also possible that adults do not want to admit, or are not aware, that children in the household are going hungry. Social desirability responding is common in survey research [50, 51], including when parents are asked to report on child behaviours [52], and it may be the case that caregivers are ashamed to admit that their children are experiencing hunger. Equally, it may be the case that parents are simply not aware of child hunger[13] [53].

If the first interpretation is accurate, however, it suggests that any measures to support caregivers and children from the effects of hunger will need to target individuals beyond the level of the household, as – at the household level – in the face of scarce resources, parents may distribute aid to children and continue to suffer themselves. A similar phenomenon is noticed in social protection grants to households affected by disability, where – in order for the individual with the disability to benefit from the grant – it has to be delivered directly to them, otherwise its benefit is 'absorbed' by the household as a whole, and the person with a disability is left at a continued disadvantage [54].

Aside from pragmatic and fungible supports, self-help and other brief interventions may be useful to target individuals most affected by low mood. Self-Help Plus (SH+), for instance, developed by WHO, is a guided multimedia psychosocial self-help package that combines a pre-recorded audio course and illustrated guide to allow very briefly trained facilitators to deliver and evidence-based intervention to many people. While it currently relies on group meetings, adaptation to this package – and others – could allow self-help, mental health promotion and treatment interventions to be delivered to people in their homes. There is a need to find scalable and sustainable ways of delivering mental health services for all different subpopulations along the continuum of affectedness, including vulnerable groups like people with preexisting mental health conditions. Mass-delivered digital interventions seem to hold promise in other settings, but need to be tested for viability in South Africa.

There is also need to reach specific risk groups with clinics and community support, including those affected by hunger, and vulnerable women and children [18]. The national government's Department of Health could classify psychological treatments as essential [55], which would reallocate resources – both financial and human – to mental health service provision (although with reallocation in the opposite direction, with mental health staff being deployed in mainstream healthcare settings to meet the need there, as well as the general lack of mental health professionals and facilities, this seems unlikely). Training paraprofessional healthcare workers – including both community- and clinic-based workers – who are currently assisting in the COVID-19 response, in basic counselling and support, may be a more feasible option [55]. This could be integrated into primary healthcare as a delivery platform, such as in a recent study in rural Kwa-Zulu Natal that shows that the ambulatory healthcare system was largely resilient during the national-wide lockdown, and visitation rates remained relatively stable [56].

13 For instance, a Study by Fram et al. [50] found that, while children reported their food insecurity with high accuracy in 4 of 6 domains, parent reports were inaccurate, missing nearly half of the children experiencing hunger.

Recommendations

Prioritise immediate relief from the acute drivers of psychological distress

It is essential that the factors which drive mental health problems, distress and cause or exacerbate mental health conditions, are addressed in the short and medium term [57]. In South Africa, these factors include job loss and unemployment, food insecurity, and the dissolution of social networks. Job creation, food support, and social safety nets such as grants could go a long way to alleviating some of the acute stress being experienced.

Make sure self-help and other sustainable mental health interventions are in place that can address the needs of large, affected populations

Social capital/social support and self-help interventions may be particularly relevant in a country like South Africa in the context of the pandemic, where the most common efforts to provide mental health support during lockdowns internationally, may not be feasible at scale. Social capital-related interventions, such as those which help people develop coping or problem-solving skills through participation in Church groups of community-based organisations, might provide people with a buffer against the stressors of the pandemic and the isolation associated with lockdowns. Additionally, "telehealth" or "mhealth" offer a contingency plan during lockdown, allowing mental health services to be offered remotely via telephone or online platforms [58]. However, in many low-resource settings, such services remain inaccessible to the people who may need them, with poor connectivity and the relative novelty of accessing help in such a manner, limiting uptake. Self-help interventions, by agencies including WHO to meet the need of remote and under-resourced populations, may overcome some of these barriers to accessing formal services.

Education about the expected psychological impact of the pandemic

If people are educated about the range of psychological experiences they may have as a result of the pandemic, and their reactions to the abnormality of the situation of a global crisis and lockdown as normalized, they may feel less distressed by their symptoms [57]. A wide range of emotional responses can be appropriately normalized by making information about usual reactions to stress widely available, and improving the mental health literacy, and coping skills, of affected people [59]. Central to such efforts, is responsible reporting.

Support health literacy communication by media

Media reports should not amplify distress, and instead focus on providing behaviour change messaging opportunities [18], such as encouraging parents to speak to their children about their feelings in reaction to the pandemic [59].

Gather better data

We need better data to inform programming and planning – immediate research priorities are to monitor and report rates of mental health conditions at both the clinical and subclinical level and to understand mechanisms and use this information to inform interventions, and this should include a focus on vulnerable groups [18].

Conclusion

The mental health of South Africans is being affected by the COVID-19 pandemic. Yet, it seems, much of this impact is driven by environmental factors. Hunger, particularly, appears to be a significant determinant of depressed mood. Addressing hunger through cash transfers, sustainable farming schemes, school feeding and other measures to combat food insecurity, need to be prioritised.

In the wake of humanitarian crises around the world, there has been a clarion call for countries to seize the opportunity of difficulty and breakdown, to create new, improved societies when they rebuild. The United Nations have coined the phrase “building back better”. In mental health, this would usually take the shape of calls to build a more resilient and inclusive public mental health system [60]. While this is undoubtedly vital, building back better in South Africa may also include a far more basic mandate: address hunger and its causes, and you will likely minimise its consequences, including mental health problems.

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