Available online at http://scik.org

Commun. Math. Biol. Neurosci. 2024, 2024:61

https://doi.org/10.28919/cmbn/8095

ISSN: 2052-2541

ON THE IMPACT OF THE COVID-19 PANDEMIC ON MENTAL HEALTH IN EGYPT: PENALIZED REGRESSION APPROACH

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Abstract: This study aims to explore the factors that affected mental health status during the COVID-19 pandemic, coupled with providing a detailed assessment of the effects of the negative economic repercussions, specifically food insecurity, changes in job activity and income levels, fear and anxiety, and strategies for coping with the pandemic.

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Received July 6, 2023

In addition, the study sheds light on how assistance provided by government agencies and non-governmental organizations enhances the mental health of individuals. The study draws upon data gathered through a survey conducted by the Economic Research Forum in Egypt during the pandemic. Using the penalized regression models, the current study showed that food insecurity, low household income, anxiety about the economic situation, and severe coping strategies for economic hardship were the primary drivers of mental health during the pandemic. In addition, some socio-demographic variables such as age, gender and place of residence played clear influences on mental health status during the pandemic. We must direct our attention and resources towards those vulnerable groups who have endured most of the mental health toll caused by the pandemic. They are in urgent need of emotional counseling and financial assistance to navigate and heal from this crisis.

Keywords: coping strategies social distancing; elastic net regression; food insecurity; LASSO; ridge regression.

2020 AMS Subject Classification: 92B15, 62J07.

1. INTRODUCTION

The COVID-19 pandemic has had an unprecedented impact on the mental health and well-being of individuals worldwide. The sudden and drastic changes to daily life, including social distancing, self-quarantine, and economic disruptions, have presented unique challenges to mental health. This study aims to explore the factors that affected mental health status during the COVID-19 pandemic, providing an in-depth analysis of the available research and evidence.

The COVID-19 pandemic has been a global health crisis, triggering far-reaching consequences for society. Beyond the effects of the pandemic on physical health, it has had a significant effect on mental health, giving rise to a" parallel pandemic of fear, anxiety, and depression"[1]. Disruption to daily routines, threat to physical health, and the feelings of uncertainty have contributed to decreased mental well-being for many individuals [2]. Understanding the factors that influence mental health during such crises is crucial for developing support systems and effective interventions. This research is dedicated to unraveling the determinants that have impacted psychological well-being amidst the COVID-19 crisis, offering a thorough scrutiny of existing studies and findings.

For the literature review and constructing the conceptual framework, a comprehensive search was conducted, ensuring the most up-to-date and relevant information. The focus was on empirical studies that provided quantitative or qualitative data on factors influencing mental health during the pandemic. Many factors have played a role in shaping mental health status during the COVID-19 pandemic. These factors are multifaceted and interconnected, and often vary across different populations and cultural contexts.

On the one hand, some Egyptian studies focused on measuring mental health during the pandemic. Arafa et al. [3] measured mental health problems such as depression, anxiety, stress, and sleep disorders in four Egyptian regions during the height of the pandemic. They identified various factors –women, non-health sector staff, those exposed to news of the pandemic, and those deprived of emotional support – that were significantly associated with increased psychological distress. Another inquiry by AboKresha et al. [4] examined the dark side of pandemic isolation, revealing an alarming increase in violence towards children and its significant psychological impact on young victims. Another study conducted by El Zoghby et al. [5] to measure mental health and social support amid the crisis, revealing that the majority reported a slight increase in family and financial challenges, with more than a third facing serious mental health impacts.

On the other hand, several researchers, including Barsoum and Majbour[6] and Abdelghani et al.[7] and Abdel-Rahman et al. [8] have studied the psychological impact of unemployment during these unprecedented times, highlighting the profound impact of job loss on psychological well-being. Although research on the consequences of COVID-19 in Arab countries is increasing, it is clear that some elements require further investigation. The negative mental health consequences of the pandemic, including forms of food insecurity, anxiety resulting from uncertainty and economic hardship, and changes in income and economic activity, have not been comprehensively investigated. Likewise, the role of subsidies, assistance, and adaptation strategies that individuals followed to deal with the pandemic, and their impact on the psychological health of individuals was not measured.

The COVID-19 pandemic has caused far-reaching consequences for mental health, and the factors

influencing mental health status are various and interconnected. This literature review has highlighted the impact of isolation and social distancing, fear and anxiety about the virus, economic hardship and losing job, grief and bereavement, uncertainty, and disruptions to daily life. Additionally, the pandemic has disproportionately impacted vulnerable populations and frontline workers, underscoring the need for effective interventions and support. Resilience and protective factors, including social connectedness and positive coping strategies, have been shown to alleviate the mental health impact of the pandemic. The rapid shift to online telehealth and mental health services has also provided opportunities for innovation and increased access to care. As the world continues to navigate the effects of the pandemic, it is crucial to build on the lessons learned and develop comprehensive strategies to support mental health.

2. CONCEPTUAL FRAMEWORK OF FACTORS INFLUENCING MENTAL HEALTH

The key factors identified in the literature are discussed as follows:

2.1 Isolation and Social Distancing

Social distancing measures implemented to limit the spread of COVID-19 have had a significant impact on social connectedness, resulting in feelings of loneliness and isolation [9]. Limiting physical contact and imposing quarantine or lockdown protocols disrupted social support systems, which are vital for maintaining mental health [10]. Several studies reported increased levels of anxiety and depression associated with prolonged periods of severe isolation [11]. For example, a longitudinal study by Killgore et al. [11] found that social isolation during the pandemic was associated with higher levels of loneliness and depressive symptoms, especially among younger adults. likewise, a cross-sectional study conducted by Wang et al. (2020) who surveyed 1,034 people in China revealed that social isolation was a significant predictor of high stress levels during the pandemic. These findings highlight the harmful effects of prolonged social distancing and isolation on mental health.

2.2 Fear and Anxiety about COVID-19

The COVID-19 pandemic has been characterized by widespread fear and anxiety related to the

virus itself [12]. Fears about infection, uncertainty about the future, and fear of losing family members have contributed to heightened anxiety and stress [13]. A systematic review by Salari et al. [14] found consistent evidence of higher anxiety levels during the pandemic, particularly among individuals with pre-existing mental health problems.

Research has also identified specific fears associated with COVID-19, such as fear of infection, fear of losing control, and fear of social isolation [12]. These concerns have been associated with increased psychological distress and poor mental health [15]. A study conducted by Zhang et al. [16] who included 1,562 Chinese adults found that fear of COVID-19 was a significant predictor of anxiety and depression, even after controlling for demographic variables.

2.3 Economic Hardship and Job Loss

The COVID-19 pandemic has had far-reaching economic consequences, with job loss, reduced income, and financial instability affecting mental health [17]. Economic hardship has been identified as a major stressor, exacerbating existing mental health problems and creating new ones [18]. A longitudinal study conducted by Abdel-Rahman et al. [8] found that individuals who experienced job loss or financial stress during the pandemic had higher levels of depression and anxiety compared to those who did not.

The impact of economic hardship on mental health may be particularly pronounced for vulnerable populations. For example, a study by Sano et al focusing on low-income households in the United States, found that financial stress during the pandemic was associated with increased psychological distress and lower levels of perceived social support [19]. Likewise, a review by Broto and Quintana-Domec [20] noted that the mental health consequences of economic shocks, such as job loss, may be more severe for individuals with pre-existing mental health problems or those with limited access to resources.

2.4 Grief and Bereavement

The COVID-19 pandemic has led to significant loss of life, and the grief and bereavement associated with it have had a profound impact on mental health [21]. The unique circumstances of the pandemic, including restrictions on gatherings and limited access to end-of-life care, have

disrupted traditional grief processes. This has led to what is called “prolonged grief,” which is characterized by intense longing or preoccupation with the deceased, feelings of disbelief, and difficulty accepting the loss [22].

Research has shown that individuals who lost loved ones during the pandemic are at increased risk of developing mental health problems such as depression, anxiety, and post-traumatic stress [16], [23]. A study conducted by Lin et al. who included 3,003 Chinese participants found that those who experienced the death of a loved one due to COVID-19 had higher levels of prolonged grief, depression, and anxiety compared to those who did not [24]. These findings underscore the need for specialized grief support and interventions during and after the pandemic.

2.5 Uncertainty and Information Overload

The COVID-19 pandemic has been characterized by a high level of uncertainty, with information and guidelines constantly evolving [25]. Uncertainty about the future, including concerns about the duration of the pandemic, the effectiveness of treatments, and the possibility of further waves of infection, has contributed to increased anxiety and stress [26]. In addition, the flow of information, often referred to as the “infodemic,” has made it difficult for individuals to learn about accurate and reliable health information [27].

A study by Gao et al. who included 486 Chinese adults found that uncertainty about the pandemic was positively associated with anxiety and depression [28]. Likewise, a qualitative study conducted by Korkmaz & Güloğlu [29] identified uncertainty as a major theme in interviews with individuals during the early stages of the pandemic, with participants expressing concerns about the future and feeling overwhelmed by the constant flow of information. Managing uncertainty and providing clear, consistent, and accessible information are critical aspects of mental health support during public health crises [25].

2.6 Resilience and Protective Factors

While the pandemic has caused many challenges to mental health, it has also highlighted the importance of resilience and protective factors. Resilience refers to the ability to adapt and deal with adversity. Several studies have identified factors that promote resilience and protect against

mental health issues during the pandemic. For example, a cross-sectional study by Dailey et al. involving 1,242 adults found that social connectedness, perceived control, and positive coping strategies were associated with lower levels of depression and anxiety during the pandemic [30]. Similarly, the study of Akbar and Aisyawati [31] revealed that social support and positive reframing were protective factors against psychological distress among Indonesia students. These findings underscore the importance of fostering resilience and identifying protective factors to mitigate the mental health impact of future crises.

2.7 Mental Health of Frontline Workers

Frontline workers, including emergency responders, healthcare professionals, and essential workers, have faced severe challenges during the COVID-19 pandemic, placing them at an increased risk of mental health issues [32]. The demanding nature of their tasks, exposure to traumatic events, and heightened risk of infection have all contributed to elevated levels of stress, anxiety, and burnout [33], [34].

A meta-analysis by Pappa et al. [32] found that frontline healthcare workers had a higher prevalence of anxiety and depression compared to the general population during the pandemic. Similarly, a qualitative study by Sim et al., [13] explored the experiences of healthcare workers in New York City and identified themes of fear, anxiety, and moral injury related to their work during the pandemic. These findings highlight the need for targeted interventions and support systems to address the unique mental health needs of frontline workers.

2.8 Mental Health of Vulnerable Populations

The COVID-19 pandemic has disproportionately affected vulnerable populations, including those with pre-existing mental or physical health conditions, racial and ethnic minorities, older adults, and individuals with lower socioeconomic status [2]. These groups often face additional stressors and barriers to accessing mental health services, exacerbating existing mental health disparities. For example, a review by Holmes et al. [2] highlighted a higher risk of mental health problems among individuals with pre-existing psychiatric disorders, with disruptions to routine and access to care contributing to increased distress. Similarly, a study by Thomeer et al., [35] found that

Black, Hispanic, and Asian respondents in the United States experienced higher levels of pandemic-related discrimination, which was associated with increased psychological distress. These findings underscore the need for targeted interventions and support for vulnerable populations to address the specific mental health challenges they face during public health crises.

2.9 Impact on Children and Adolescents

The COVID-19 pandemic has also had affected the mental health of children and adolescents [36], [37]. School closures, disruptions to routines, and social isolation have all contributed to increased stress and anxiety among young people [38]. Additionally, concerns about family members' health and exposure to stressful environments may have adversely affected their mental well-being (Racine et al., 2021).

A meta-analysis by Ma et al., [38] found that children and adolescents experienced elevated levels of depression and anxiety during the pandemic, with a higher risk among those with pre-existing mental health issues. Similarly, a qualitative study by Racine et al. [36] explored the experiences of Canadian children and youth during the pandemic, identifying figures of social isolation, disrupted routines, and increased family stress, all of which affected their mental health. These findings underscore the need for age-appropriate mental health support and interventions for youth during public health emergencies.

2.10 Mental Health Services and Telehealth

The COVID-19 pandemic has badly affected the delivery of mental health services, with disruptions to face-to-face appointments and a rapid shift to telehealth and online services [39]. Telehealth, which involves the use of digital technologies to provide mental health care remotely, has emerged as a vital tool to ensure continuity of care during the pandemic. Research has highlighted that telehealth interventions can be effective in providing mental health support during the pandemic. A review by Gajarawala and Pelkowski [40] found that telehealth interventions improved symptoms of anxiety and depression and increased access to care, especially for individuals in rural or underserved areas. However, barriers to accessing telehealth services have also been identified, such as limited technological resources or digital literacy, [40]. Addressing

these barriers and ensuring equitable access to mental health services, during and after the pandemic, is crucial.

3. METHODS

3.1 Data Source

The research utilizes data from the Combined COVID-19 Middle East and North Africa Monitor Household Survey (CCMMHH), which provides a wide-ranging picture of the COVID-19's impacts. This survey is carried out by the Economic Research Forum (ERF) and reached out to individuals between the ages of 18 and 64 who own mobile phones. The process of calling a randomly generated list of phone numbers was repeated up to three times, if necessary, to successfully administer the survey. The ERF successfully recruited around 4007 participants in Egypt. In the analytical phase, individual weights were applied to consider the complex aspects of the survey methodology. To dive deeper into the sampling technique, response ratios, compilation of the data, scaling factors, structure of the survey, and the detailed segments within the query form, one can refer to document (29).

3.2 Outcome Variable

The tool used to measure subjective wellbeing is the World Health Organization Well-Being Index, commonly abbreviated as WHO-5. This index takes a positive angle on mental health, aiming to capture an individuals' experiences of positive states. It does so by investigating participants' reflections on five statements that relate to their lived experiences over the last fourteen days. These statements are focused on the feelings of cheerfulness and good spirits, calmness and relaxation, vitality and energy, waking up fresh and well-rested, and engagement with interesting aspects of day-to-day life. Participants indicate the frequency of these feelings on a scale from "none of the time" (scored as 1) to "all of the time" (scored as five). The initial scores, which can sum up to 30, where 5 signifies the lowest level of wellbeing and 30 denotes the highest.

3.3 Independent Variables

Past research has shown that an individual's mental well-being is often shaped by their socio-

demographic background. The factors considered in our study, include gender, whether someone lives in a city or countryside, age, education level – spanning from less than education to higher education - as well as marital status, from single through married, to separated or divorced.

Our aim includes assessing the detrimental impacts of the COVID-19 pandemic on mental health conditions, which encompasses aspects such as the enforcement of isolation and social distancing measures, encountering food insecurity, experience fears and anxiety, and the reduction of family earnings. The practice of social distancing is evaluated through three dichotomous variables that denote whether an individual engaged in specific behaviors: maintaining a distance of at least one meter from others, utilizing a mask covering when outside the home, and increasing hand hygiene frequency relative to pre-pandemic norms.

Concerning food security, we utilize a binary variable to determine if an individual has faced challenges in accessing sufficient food during the pandemic. An individual is considered to suffer from food insecurity if he faces any obstacle, whether this is related to the problem of accessing the food market due to restrictions on movement or purchasing the usual amount of food either due to a shortage in the markets or an increase in prices, or exposure to a decrease in income. We evaluate changes in household income in the past month when compared to the financial situation in February of 2020. Changes include an increase, stability, or decrease in income, allowing us to accurately assess the various effects of the pandemic on individuals' financial and psychological well-being.

We also use a bivariate approach to measure concerns related to the coronavirus. This entails recording the extent to which individuals worry about contracting the virus and their level of concern about the economic impacts of the pandemic. They express their concerns numerically on a scale from one to four, where "not at all concerned" represents "not at all worried" and four represents "very worried."

The paper also focuses on measuring the impact of the coping strategies that individuals followed to deal with the negative economic repercussions of losing income and jobs on their mental health status. It includes depleting savings, asking for help from family and friends whether inside the

country or abroad, being forced to return to the country, borrowing from banks or employers, or selling assets and property. On the other hand, we explain the impact of receiving aid from the government, civil society organizations, and others on the mental health status of individuals. Government aid includes support from the Takaful/Karama Program, ration cards, cash aid, and irregular workers' grant.

3.4 Statistical Analysis

Frequency distribution and descriptive statistics (mean ± SD) were used to describe mental health scores according to the characteristics of study participants. Statistical differences in mental health scores across categorical variables of 2 or 3 categories were examined using the t test and AVOVA test, respectively. The results were considered significant with a p-value less than 0.05. Statistical analysis is performed using R software version 4.1.1.

This study depended on the penalized regression models to identify the most contributing variables and exclude irrelevant variables. The shrinking approach built in penalized models reduces the number of independent variables and constrains the coefficient estimates. Penalized models produce more interpreted models and enhance the fit through reducing the variance. The ridge regression, lasso, and elastic net regression are applied.

Ridge regression used a similar technique to the linear regression model with minimizing a slightly different quantity of the coefficients estimates. Ride regression modifies the loss function by including a penalty parameter to reduce the model's complexity. The coefficients estimate of the ridge regression $\hat{\beta}^R$ are the values that minimize:

$$\sum_{i=1}^{n}(y_i - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p}\beta_j^2 = \|\mathrm{y} - \mathrm{X}\beta\|^2 + \lambda\|\beta\|^2, \quad (1)$$

where y is a vector of the observed values of the dependent variable, X is the design matrix containing independent variables, β is the vector of regression parameters we want to estimate, $\|\mathrm{y} - \mathrm{X}\beta\|^2 = \sum_{i=1}^{n}(y_i - \sum_{j=1}^{p}\beta_j x_{ij})^2 = RSS$ is the residual sum of squares, which measures the deviation between the observed values y and the predicted values Xβ from the linear model, $\lambda \geq 0$ is the regularization (tuning) parameter that controls the overall strength of the penalty term. A

larger λ implies more shrinkage/regularization, and $\|\beta\|^2 = \sum_{j=1}^{p} \beta_j^2$, where $\lambda \sum_{j=1}^{p} \beta_j^2$ is the shrinkage penalty. Ridge regression trades off two different criteria. While ridge regression seeks to estimate the β that fits the data well by minimizing the RSS as with the least squares procedure, there is a shrinkage penalty which will be small when β are close to zero. λ controls the relative effects of the two terms (RSS and shrinkage penalty) on the coefficient estimates. When λ equals zero, the estimates of ridge regression and least squares are the same. However, as the λ increase, the effect of the shrinkage penalty increase, and estimates shrinks toward zero. Ridge regression produces different coefficient estimates $\hat{\beta}_\lambda^R$ corresponding to different values of λ. Cross-validation procedure is used to select the best value of λ that achieve the smallest mean squared error (MSE).

While the ridge regression keeps all predicators in the final model as λ shrinks the coefficients without setting any of them equal to zero, LASSO regression (Least Absolute Shrinkage and Selection Operator regression) presents an obvious advantage over the ridge regression, allowing getting rid of the weakly influential covariates. LASSO penalizes the sum of the absolute values of the coefficients, whereby they equal zero for high values of λ. We apply both ridge and LASSO regressions and compare them. Ridge regression gives us initial insight into which variables are weakly correlated with the outcome variable and provides their shrinking estimates. Whereas, lasso regression enables the exclusion of irrelevant variables, maintaining the influential ones. LASSO generates more interpretable models by shrinking the estimates to zero when the tuning parameter (λ) is sufficiently large. The coefficients estimate of the LASSO regression $\hat{\beta}^L$ are the values that minimize:

$$\sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{p} \beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| = \|\mathrm{y} - \mathrm{X}\beta\|^2 + \lambda \|\beta\|_1, \quad (2)$$

where $\|\beta\|_1 = \sum_{j=1}^{p} |\beta_j|$. The difference between Ridge and lasso formulations is that the β_j^2 in the ridge regression penalty has been replaced by $|\beta_j|$ in the lasso penalty. The cross-validation error is computed for a different value of λ and to select the one that have the smallest cross-validation.

The elastic net appeared to address the problem of unstable lasso results due to the selection of variables based on the nature of the data. Elastic net is based on a combination of ridge steepness and lasso penalties to get the best estimates. Stated differently, the elastic net is a regularization and variable selection strategy that leverages the advantages of both L1 norm (lasso penalty) and L2 norm (ridge penalty) by combining them linearly. Combining these two drawbacks gives the elastic net a pleasant middle ground:

1) It can select or exclude sets of related variables together, getting around the restriction of the lasso.

2) It allows for automatic variable selection by generating sparse models like lasso.

The elastic net penalty is controlled by two tuning parameters: the mixing parameter α that decides the convex combination of lasso and ridge penalties, and the regularization parameter λ that controls the overall strength of the penalty as follows:

$$\|y - X\beta\|^2 + \lambda \left[(1-\alpha)\frac{1}{2}\|\beta\|^2 + \alpha\|\beta\|_1\right], \quad (3)$$

where $0 < \alpha < 1$. It controls the balance between the ridge and lasso penalties. We can note that if α = 0 corresponds to ridge regression (L2 penalty only), and if α = 1 corresponds to lasso regression (L1 penalty only). But if $0 < \alpha < 1$ is the elastic net penalty (combination of L1 and L2). So, the elastic net objective function combines the residual sum of squares (RSS) with the elastic net penalty term that is a linear combination of the ridge and lasso penalties, controlled by α and λ.

4. RESULTS

4.1 Descriptive Analysis

A total of 4,007 individuals participated in the survey. The average age of the respondents is 35.15 years, with a standard deviation of 11.21 years. As indicated in Table 1 Men made up the majority at 63.5%, with a large segment, 71%, indicating that they were married. The distribution between urban and rural residents was almost equal, at 51% and 48% respectively. About 47% of the sample had a secondary education. Mental health status differed significantly according to demographic

characteristics, it was worse for urban residents, males, and divorced/widowed individuals. However, the differences between males and females in average mental health scores disappear in urban areas, as shown in Figure 1, as well as at levels of both basic and higher education, as shown in Figure 2.

Survey respondents reported facing a range of food security challenges. Nearly 13% found themselves unable to access markets due to government restrictions on movement, and 20% faced the same problem due to food shortages. Nearly half of the participants (47%) said that rising prices had affected their ability to purchase usual food items, and a similar percentage (48%) indicated that their food intake had been affected by a decline in their income. Nearly 43% had to reduce their meal portions.

A minority of 13% reported changing their economic activity in response to the effects of the pandemic. Regarding financial stability, 44% of survey participants reported no change in income, however, 46% suffered a decline, and only 10% saw their earnings increase during this period. All forms of food insecurity, changing economic activity and decreasing income cause a significant decrease in individuals' mental health scores, as indicated in Table 1. At all levels of changes in household income during the pandemic, males and rural residents maintain higher mental health scores and the differences between individuals increases when household income increases by more than 25%, as indicated in Figure 3 and Figure 4.

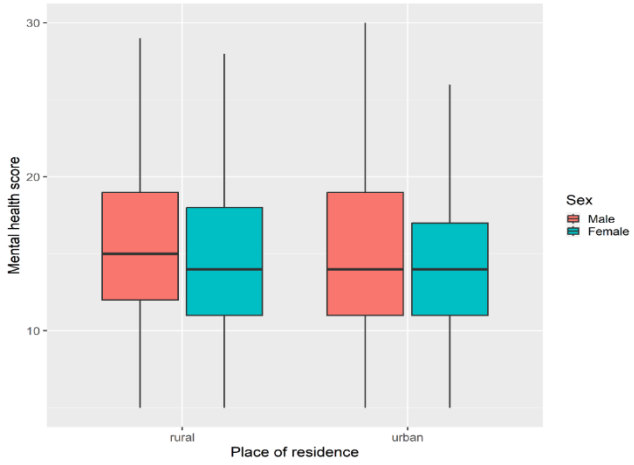

Figure 1: Average mental health score according to place of residence and sex

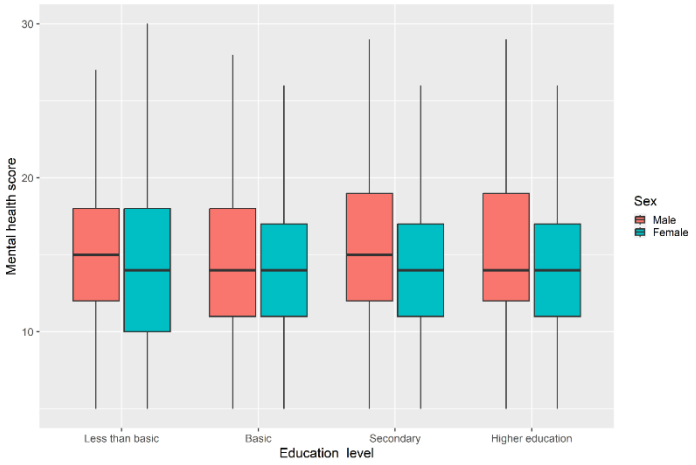

Figure 2: Average mental health score according to education level and sex

A quarter of respondents were very worried about infection, compared to 36% who were not worried at all. 19.3% are very worried about the economic situation, compared to 19.8% who are not worried at all. Most of the respondents applied isolation and social distancing measures and infection **prevention** methods. Anxiety and fears related to the pandemic had a significant impact on mental health scores, in contrast to distancing and isolation measures, they did not show a significant impact.

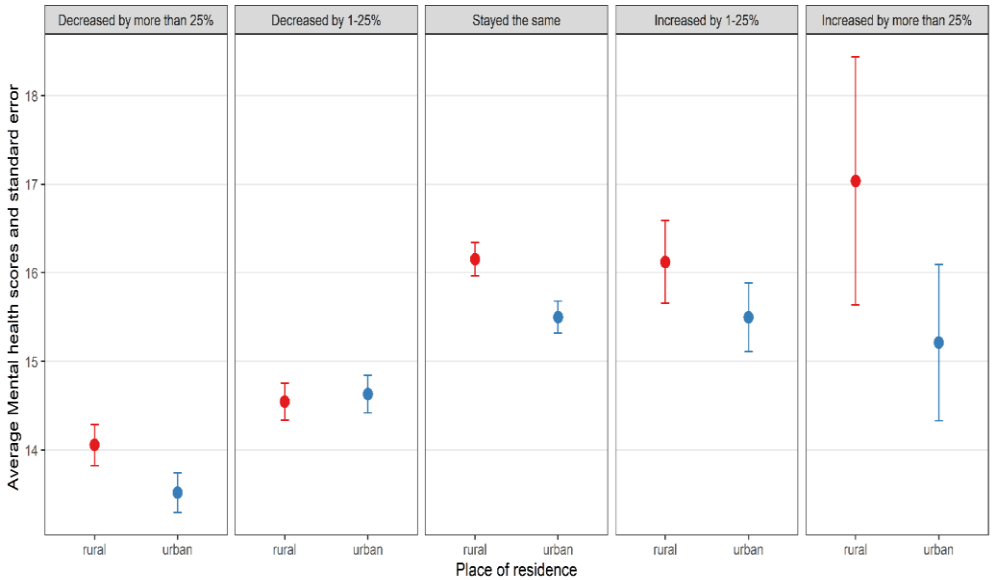

Figure 3: Average mental health score according to sex and changes in household income

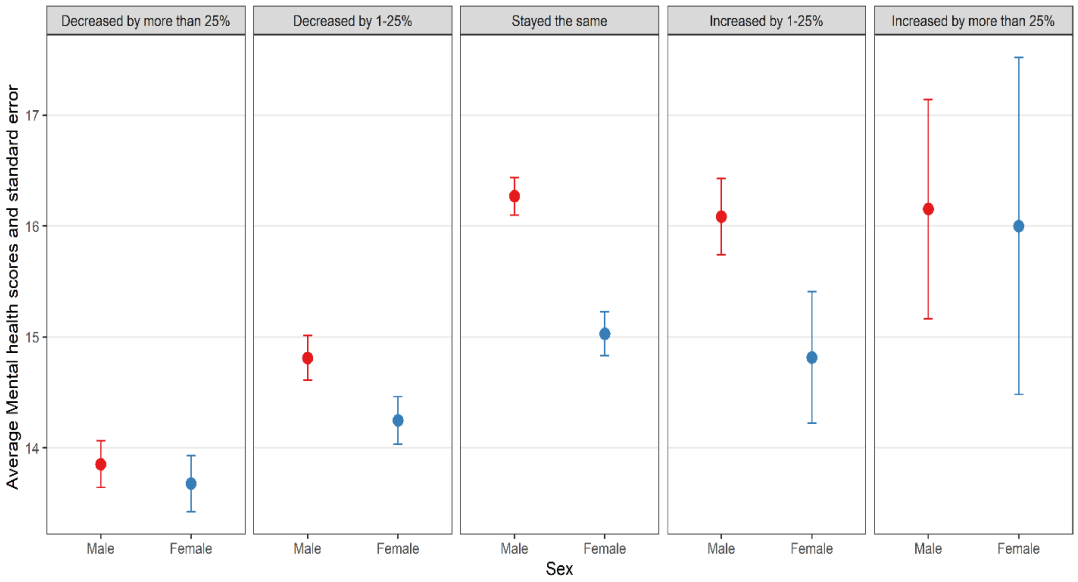

Figure 4: Average mental health score according to place of residence and changes in household income

Table 1: Distribution of respondents according to their demographic characteristics and mental health scores

Variable	**Mental health Mean ± SD**	**Test statistic & P-value**	**n(%)**
Demographic characteristics			
Gender			
Male	15.38±5.41	$t = 5.26$	1462(36.5)
Female	14.51±4.79	p-value = 0.0001***	2545(63.5)
Place of residence			
Urban	14.85±5.19		2077(51.8)
Rural	15.28±5.23	$t = 2.59$	1930(48.2)
Education		p-value = 0.009**	
Less than basic	15.00±5.56		687(17.1)
Basic	14.63±4.86		507(12.7)
Secondary	15.16±5.17	$F = 1.48$	1866(46.6)
Higher	15.16±5.23	p-value = 0.217	947(23.6)
Marital status			
Never married.	15.46±5.17		963(24.0)
Currently married.	14.97±5.19	$F = 4.65$	2866(71.5)
Widowed/ divorced	14.43±5.68	p-value = 0.01**	178(4.4)

Economic Hardship			
Difficulty accessing the food market due to movement restrictions/closure			
Yes	13.42±4.59	$t = 5.89$	533(13.3)
No	14.91±4.89	p-value = 0.0001***	3474(86.7)
Difficulty purchasing the usual amount due to food shortages in the markets			
Yes	13.68±4.67	$t = 6.69$	804(20.1)
No	14.96±4.90	p-value = 0.0001***	3203(79.9)
Difficulty purchasing the usual quantity due to price increases.			
Yes	13.77±4.29	$t = 11.98$	1866(46.6)
No	15.52±5.23	p-value = 0.0001***	2141(53.4)
Difficulty purchasing the usual quantity due to decline income.			
Yes	13.65±19.19	$t = 13.36$	1911(47.7)
No	15.71±5.13	p-value = 0.0001***	2096(52.3)
Having to reduce the usual amounts of food.	13.67±4.23	$t = 12.62$	1723(43.0)
Yes	15.50±5.08	p-value = 0.0001***	2284(57.0)
No			
The status of the main job/activity during COVID-19 compared to before.			
Similar	15.25±5.35	$t = 3.43$	2709 (86.7)
Different	14.34±4.97	p-value = 0.01**	415 (13.3)
Change in total monthly household income last month compared to before the pandemic.	13.78±4.89		923 (23.0)
	14.59±4.52		925 (23.1)
Decreased by more than 25%	15.55±5.46	$F = 27.65$	1763 (44.0)
Decreased by 1-25%	15.78±5.52	p-value = 0.0001***	341(8.5)
did not change	16.11±6.09		55(1.4)
1-25% increase			
Increase by more than 25%			
Fear and Anxiety about COVID-19			
Anxiety about being infected with COVID-19	15.83±5.97		1428 (35.6)
Not at all worried	15.42±4.59		608 (15.2)
Little worried	14.89±4.62	$F = 20.04$	812 (20.3)
Rather worried	14.09±4.74	p-value = 0.0001***	1024(25.6)
Very worried	13.78±4.53		135(3.4)
I had COVID-19			

Anxiety about the economic situation	17.06±6.38		795(19.8)
Not at all worried	15.61±4.82		666 (16.6)
Little worried	15.14±4.64	$F = 73.18$	774(19.3)
Rather worried	13.93±4.67	p-value = 0.0001***	1772 (44.2)
Very worried			
Isolation and Social Distancing			
Staying at least one meter away from people	15.07± 5.12	$t = 0.119$	3466(86.5)
Yes	15.04±5.76	p-value = 0.906	541 (13.5)
No			
Wearing a mask outside the house			
Yes	15.11±5.20	$t = 1.58$	3545 (88.5)
No	14.70±5.30	p-value = 0.114	462 (11.5)
washing hands with soap more often than before		$t = 0.669$	
Yes	15.09±5.13	p-value = 0.504	3460 (86.3)
No	14.91±5.71		547 (13.7)
Total	15.06 ±5.21	-----	4007 (100)

Note: *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001.

The pandemic caused individuals to resort to adaptation strategies to deal with its negative repercussions. As indicated in Table 2, 33% of respondents spent their savings, 40% resorted to family and friends, 20% returned to their original place of residence, 14% borrowed, and 20% sold their assets and property. All coping strategies had a significant negative impact on the mental health of individuals.

To mitigate the effects of the pandemic on individuals, the government and civil society organizations provided financial and in-kind aid to individuals. 5.7% received support from the Takaful/Karama program, 1% utilized ration cards to obtain food commodities at reduced prices, 6% received financial support from relatives inside the country, while a very small percentage, not exceeding 1%, received support from civil society organizations. All types of aid did not have a significant effect on the mental health of individuals, except for receiving aid from relatives at home.

Table 2: Strategies for coping with the pandemic, types of support, and scores of mental health associated with them

Variables	**Mental health Mean ± SD**	**Test statistic & p-value**	**n(%)**
Coping with the economic situation during the pandemic Spent savings			
Mentioned	14.51±4.80	$t = 4.94$	1325(33.1)
Not mentioned	15.34±5.38	p-value = 0.0001***	2682 (66.9)
Resorting to family/friends in country			
Mentioned	14.34±4.77	$t = 7.47$	1610 (40.2)
Not mentioned	15.55±5.44	p-value = 0.0001***	2397 (59.8)
Resorting to Family/friends abroad			
Mentioned	14.54±4.44	$t = 1.75$	212 (5.3)
Not mentioned	15.09±5.25	p-value = 0.081	3795(94.7)
Back to village/family			
Mentioned	14.38±4.75	$t = 2.24$	781(19.5)
Not mentioned	15.15±5.31	p-value = 0.026*	3226 (80.5)
Borrowing bank/employer/lender			
Mentioned	14.32±4.99	$t = 3.69$	550(13.7)
Not mentioned	15.18±5.23	p-value = 0.0001***	3457(86.3)
Selling assets			
Mentioned	14.11±4.94	$t = 5.96$	783 (19.5)
Not mentioned	15.29±5.25	p-value = 0.0001***	3224(80.5)
Receiving finical support from government Takaful/Karama program			
Mentioned	15.14±5.03	$t = 0.287$	299(7.5)
Not mentioned	15.06±5.22	p-value = 0.767	3708(92.5)
Ration cards			
Mentioned	15.09±5.19	$t = 0.566$	3094 (77.2)
Not mentioned	14.97±5.26	p-value = 0.57	913 (22.8)
Cash			
Mentioned	15.27±5.68	$t = 0.991$	18 (0.4)
Not mentioned	15.06±5.21	p-value = 0.160	3989 (99.6)
Exceptional allowance for irregular worker			
Mentioned	14.40±4.72	$t = 1.37$	114 (2.8)
Not mentioned	15.08±5.22	p-value = 0.17	3893 (97.2)
Receiving unusual social support from Church/mosque			
Mentioned	14.58±4.64	$t = 0.576$	38 (0.9)
Not mentioned	15.07±5.22	p-value = 0.565	3969 (99.1)

Relatives in country			
Mentioned	14.28±4.97	$t = 2.35$	236(5.9)
Not mentioned	15.11±5.23	p-value = 0.02*	3771 (94.1)
Relatives abroad			
Mentioned	15.11±4.98	$t = 0.047$	39 (1.0)
Not mentioned	15.06±5.21	p-value = 0.963	3968(99.0)
MP/Politican			
Mentioned	13.72±4.61	$t = 0.851$	11 (0.3)
Not mentioned	15.07±5.21	p-value=0.358	3996 (99.7)
NGO/CSO			
Mentioned	15.65±5.70	$t = 0.645$	32 (0.8)
Not mentioned	15.06±5.21	p-value = 0.559	3975 (99.2)

Note: *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001. SD: standard deviation.

4.2 Results of Penalized Regression Models

The next section presents the outcomes of the three penalized regression models. The three models are contingent upon the tuning parameter (λ); hence they are executed within a range of λ values spanning from 10E-3 to 10E+9. Each value of λ relates to a vector of coefficients. The data is partitioned into two distinct sets, namely the training set and the test set, to accurately estimate the test error. The ten-fold cross-validation approach is employed to identify the ideal value of λ that yields the minimum mean squared error (MSE).

1- Ridge Regression Model

The ridge regression model is fitted on the training data and MSE is estimated on the test data. The smallest MSE is achieved at λ equals 0.613591 as indicated in Figure 5. Figure 5 shows to be showing the MSE as a function of the logarithm of λ. The MSE initially decreases as $log(\lambda)$ increases from a negative value, indicating that some amount of regularization helps reduce the MSE. However, when $log(\lambda)$ continues increasing, the MSE starts rising again, which suggests overfitting due to too much regularization. This figure highlights the importance of tuning the regularization parameter (λ) appropriately to balance underfitting and overfitting for optimal model performance.

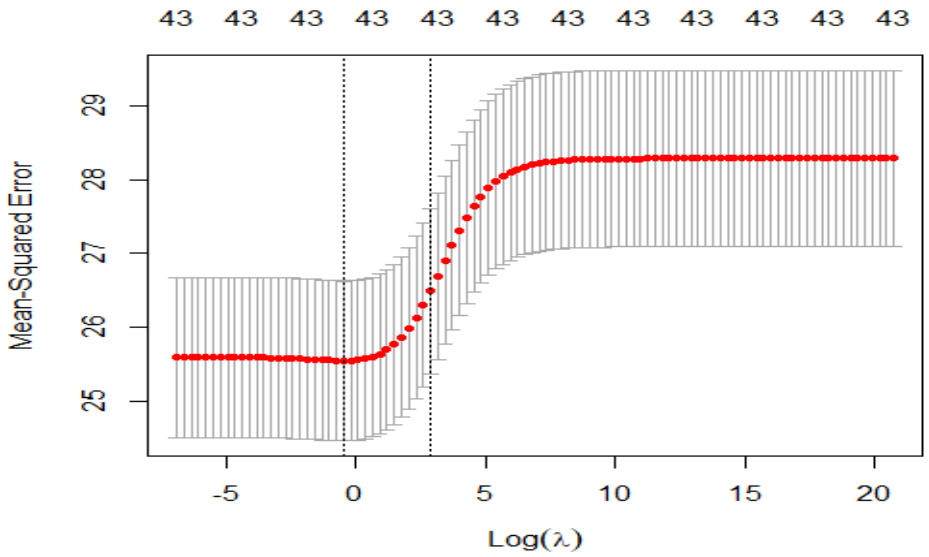

Figure 5: Cross-validation selection of λ and corresponding MSE in ridge model ($\lambda = 0.613591$)

Based on the ridge regression results presented in Table 3, we can note that the ridge regression model is significant because the p-value of F-value is less than 0.01. The following points summarize the main findings regarding the impact of the COVID-19 pandemic on mental health in Egypt based on the model estimated using the ridge regression technique:

1. The factors that had a significant negative impact on mental health during the pandemic were severe anxiety about the economic situation, anxiety about contracting COVID-19, difficulty obtaining usual amounts of food due to price increases or decreased income and having to reduce usual food amounts.

2. Maintaining the main job/activity and an increase in household income during the pandemic contributed to better mental health.

3. There was no significant impact of education level, marital status, or receiving aid on mental health according to these results.

4. Adopting coping strategies such as relying on savings and friends/relatives in the country had a negative impact on mental health.

Overall, these ridge regression results indicate that economic factors and anxiety towards COVID-

19 were among the major determinants of mental health during the pandemic in Egypt. However, LASSO and elastic net regression techniques will be performed to select the best estimation model for the mental health score.

Table 3: Results of the ridge regression of the factors predicting mental health scores

Variable	**Estimate**	**SE**	**t-value**	**p-value**
Intercept	18.72	0.59	31.68	0.0001***
Age	-0.02	0.01	-1.94	0.052*
Female	-0.34	0.20	-1.71	0.086*
Urban residents	-0.30	0.19	-1.59	0.109
Education level				
Basic education	-0.81	0.34	-2.33	0.019**
Secondary education	-0.07	0.27	-0.28	0.775
Higher education	-0.22	0.31	-0.70	0.480
Marital status				
Currently Married	-0.08	0.26	-0.28	0.771
Widowed/divorced	-0.18	0.52	-0.33	0.734
Food insecurity				
Had difficulty accessing the food market due to movement restrictions	-0.06	0.29	-0.22	0.818
Had difficulty purchasing the usual amount due to food shortages in the markets	-0.15	0.26	-0.59	0.551
Had difficulty purchasing the usual quantity due to price increases.	-0.63	0.22	-2.83	0.004***
Had difficulty purchasing the usual quantity due to decline income	-0.65	0.24	-2.74	0.006***
Had to reduce the usual amounts of food	-0.72	0.22	-3.35	0.000***
Maintained the main job/activity during COVID-19 as before	0.76	0.27	2.79	0.005***
Income changes	0.39	0.28	1.43	0.152
Income decreased by 1-25%				
Income stayed the same	0.65	0.26	2.52	0.01**
Income increased by 1-25%	0.89	0.36	2.44	0.01**
Income increased by more than 25%	1.01	0.75	1.35	0.175
Anxiety about being infected with COVID-19				
little worried	-0.28	0.28	-0.98	0.326
Rather worried	-0.80	0.27	-2.97	0.002***
Very worried	-0.91	0.26	-3.46	0.000***
I had it already	-1.49	0.52	-2.85	0.004***

Anxiety about the economic situation				
little worried	-1.42	0.31	-4.59	0.0001***
Rather worried	-1.46	0.31	-4.68	0.0001***
very worried	-2.34	0.27	-8.66	0.0001***
Isolation and Social Distancing				
Don't Stay at least one meter away from people	-0.23	0.28	-0.81	0.0001***
Don't wear a mask outside the house	-0.24	0.31	-0.77	0.440
Don't wash hands with soap more often than before	-0.70	0.27	-2.52	0.011**
Receive aid and support				
Aids from Takaful/Karama	0.48	0.35	1.34	0.179
Had Ration cards	0.12	0.22	0.52	0.597
Received Cash	-0.14	1.68	-0.08	0.932
Exceptional allowance for irregular worker	-0.57	0.55	-1.02	0.305
Support from Church/mosque	-0.54	1.02	-0.52	0.599
Support from Relatives in country.	0.38	0.45	0.82	0.408
Support from Relatives abroad	0.59	1.47	0.40	0.684
Support from MP/Politician	0.67	1.72	0.38	0.697
Support from NGO/CSO	1.23	1.15	1.06	0.287
Coping with the economic situation				
Spent savings	-0.43	0.19	-2.15	0.031**
Family/friends in country	-0.57	0.19	-2.84	0.004***
Family/friends abroad	0.08	0.42	0.19	0.845
Back to village/family	0.20	0.24	0.84	0.396
Borrowing bank/employer/lender	-0.49	0.26	-1.85	0.063*
Selling assets	-0.42	0.23	-1.79	0.072*
Goodness of fit test (F-test)				
F-value (df1 = 43, df2 = 3080)	10.05	p-value of F		0.0001***

Note: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. SE: standard error of estimate. df1: the degrees of freedom associated with the numerator in the F-ratio calculation; df2: the degrees of freedom associated with the denominator in the F-ratio calculation. Reference categories of the variables are male, rural, basic education, never married, not being exposed to this difficulty in all variables of food insecurity, had to change the main activity/job, household income decreased by more than 25%, Not at all worried in anxiety variables, Commitment to implementing this procedure in social distancing variables, did not receive this assistance or support, did not follow the mentioned coping strategy.

2- LASSO Regression Model

Like the ridge model, the LASSO regression model is fitted on the training data and MSE is estimated on the test data. The smallest MSE is achieved at λ equals 0.065793 as indicated in Figure 6.

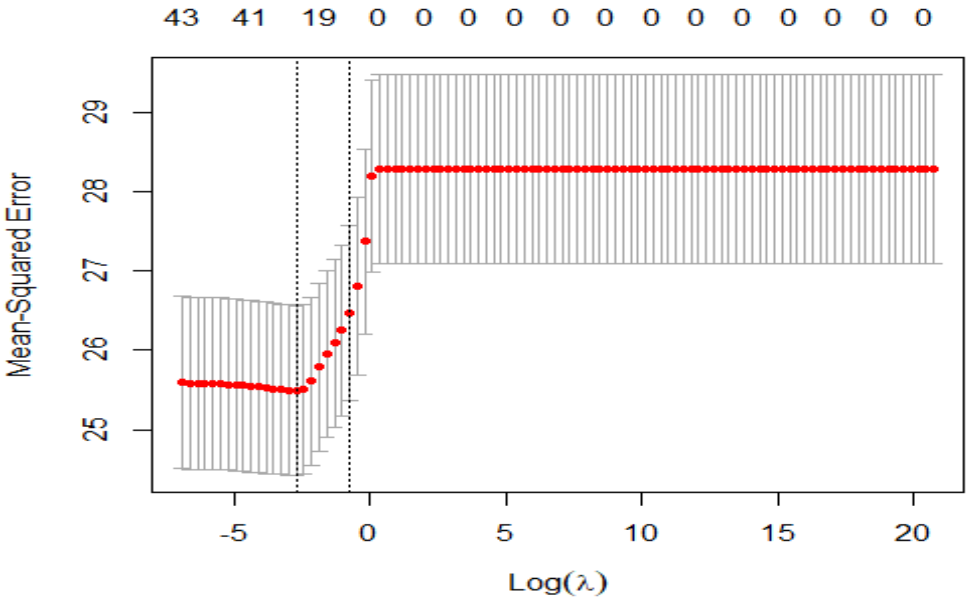

Figure 6: Cross-validation selection of λ and corresponding MSE in LASSO model ($\lambda = 0.065793$)

Based on the LASSO regression results presented in Table 4, we can note that the LASSO regression model is significant because the p-value of F-value (with df1 = 30; df2 = 3093) is less than 0.01. The following points summarize the main findings regarding the impact of the COVID-19 pandemic on mental health in Egypt based on the model estimated using the LASSO regression technique:

1. The LASSO model has fewer predictors compared to the ridge regression model in Table 3, as it performs variable selection and shrinks some coefficients to zero.

2. Similar to ridge regression, factors like difficulty purchasing usual food amounts due to price increases or income decline, having to reduce food amounts, anxiety about the economic situation, and anxiety about contracting COVID-19 have significant negative impacts on mental health

scores.

3. Maintaining the main job/activity during the pandemic and an increase in household income are associated with better mental health, as observed in the ridge regression results.

4. The LASSO model suggests that factors like age, being female, urban residence, and basic education level have significant negative effects on mental health during the pandemic.

5. Coping strategies like spending savings, relying on family/friends in the country, borrowing, and selling assets are negatively associated with mental health scores, similar to the ridge regression findings.

6. Factors like marital status, receiving aid, and support from NGOs/CSOs do not appear to have significant impacts on mental health in the LASSO model.

7. Compliance with social distancing measures, such as not wearing a mask outside or not washing hands more frequently, has a negative impact on mental health according to the LASSO results.

8. The LASSO model has a slightly higher F-value (14.26) compared to the ridge regression model (10.05), indicating a better overall fit.

Overall, the LASSO regression results reinforce the importance of economic factors, food insecurity, anxiety towards COVID-19, and job stability in determining mental health outcomes during the pandemic in Egypt. Additionally, it highlights the potential negative impacts of certain coping strategies and non-compliance with social distancing measures on mental health. However, the elastic net regression technique will be implemented to compare the results of the LASSO model with the results of the elastic net model, because the elastic net model combines the strengths of ridge regression (controlling multicollinearity) and LASSO regression (variable selection) to identify the most important predictors of mental health scores during the COVID-19 pandemic in Egypt.

Table 4: Results of the LASSO regression of the factors predicting mental health scores

Variable	**Estimate**	**SE**	**t-value**	**p-value**
Intercept	18.89	0.54	34.94	0.0001***
Age	-0.02	0.01	-2.51	0.012**
Female	-0.37	0.19	-1.91	0.056*
Urban residents	-0.31	0.18	-1.67	0.093*
Education level				
Basic	-0.77	0.34	-2.26	0.023**
Secondary	-0.049	0.27	-0.18	0.855
Higher education	-0.19	0.31	-0.62	0.533
Food insecurity				
Had difficulty purchasing the usual amount due to food shortages in the markets	-0.17	0.25	-0.67	0.501
Had difficulty purchasing the usual quantity due to price increases.	-0.64	0.22	-2.86	0.004***
Had difficulty purchasing the usual quantity due to decline income	-0.67	0.24	-2.86	0.004***
Had to reduce the usual amounts of food	-0.74	0.22	-3.42	0.001***
Maintained the main job/activity during COVID-19 as before	0.79	0.27	2.93	0.003***
Income changes				
Income Stayed the same	0.44	0.21	2.077	0.037**
Income Increased by 1-25%	0.66	0.33	2.00	0.045**
Income Increased by more than 25%	0.83	0.73	1.13	0.256
Anxiety about being infected with COVID-19				
Rather worried	-0.68	0.25	-2.74	0.006***
Very worried	-0.80	0.24	-3.32	0.001***
I had it already	-1.39	0.51	-2.70	0.006***
Anxiety about economic situation				
little worried	-1.46	0.30	-4.85	0.0001***
Rather worried	-1.50	0.30	-4.89	0.0001***
very worried	-2.39	0.27	-9.02	0.0001***
Isolation and Social Distancing				
Don’t wear a mask outside the house	-0.25	0.29	-0.85	0.392
Don’t wash hands with soap more often than before	-0.72	0.27	-2.64	0.008***
Aid and support				
Aids from Takaful/Karama	0.45	0.35	1.26	0.206

Exceptional allowance for irregular worker	-0.58	0.55	-1.05	0.293
Support from NGO/CSO	1.31	1.13	1.15	0.247
Coping with the economic situation				
Spent savings	-0.45	0.19	-2.24	0.024**
Family/friends in country	-0.55	0.19	-2.80	0.005***
Back to village/family	0.26	0.24	0.94	0.346
Borrowing bank/employer/lender	-0.47	0.27	-1.76	0.078*
Selling assets	-0.42	0.23	-1.80	0.071*
Goodness of fit test (F-test)				
F-value (df1 = 30; df2 = 3093)	14.26	p-value of F		0.0001***

Note: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. SE: standard error of estimate. df1: the degrees of freedom associated with the numerator in the F-ratio calculation; df2: the degrees of freedom associated with the denominator in the F-ratio calculation.

3- Elastic Net Regression Model

Like the ridge and LASSO models, the elastic net model is fitted on the training data and MSE is estimated on the test data. When α equals 0.25, the smallest MSE is achieved at λ equals 0.20092 as indicated in Figure 7.

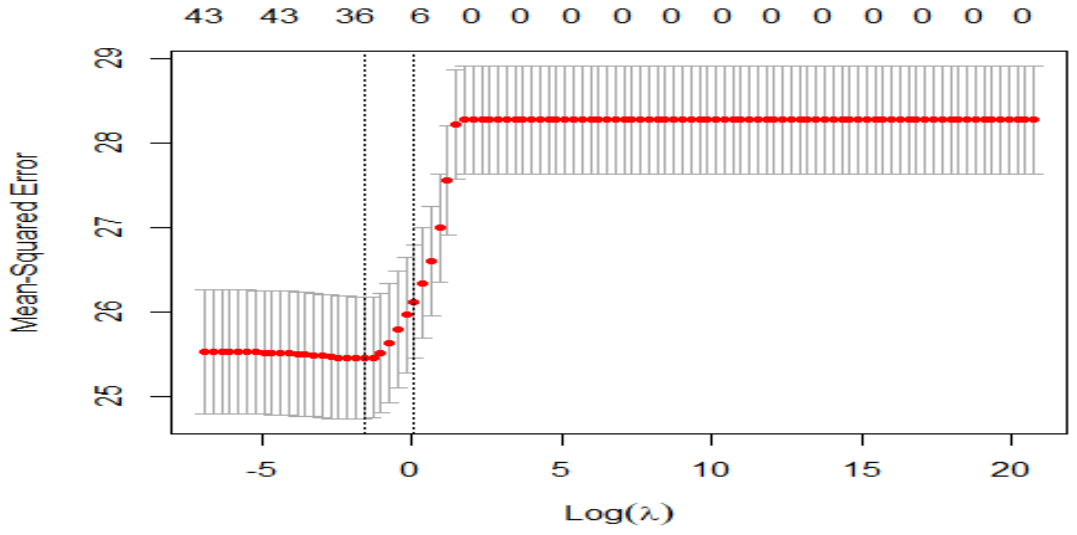

Figure 7: Cross-validation selection of λ and corresponding MSE in elastic net model ($\alpha = 0.25,\ \lambda = 0.20092$)

Based on the elastic net regression results presented in Table 5, we can provide the following comments:

1. Like the previous models, factors such as difficulty purchasing usual food amounts due to price increases or income decline, having to reduce food amounts, anxiety about the economic situation, and anxiety about contracting COVID-19 have significant negative impacts on mental health scores.
2. Maintaining the main job/activity during the pandemic and an increase in household income are associated with better mental health outcomes, consistent with the previous findings.
3. The elastic net model suggests that factors like age, being female, urban residence, and having a basic education level have significant negative effects on mental health during the pandemic.
4. Coping strategies like spending savings, relying on family/friends in the country, borrowing, and selling assets are negatively associated with mental health scores, reinforcing the earlier observations.
5. Factors like marital status, receiving aid, and support from NGOs/CSOs do not appear to have significant impacts on mental health in the elastic net model.
6. Non-compliance with social distancing measures, such as not washing hands with soap more often, has a negative impact on mental health according to the elastic net results.
7. The elastic net model has the highest F-value (16.37) compared to the ridge regression (10.05) and LASSO (14.26) models, indicating the best overall fit among the three models.

Overall, the elastic net regression results reinforce the importance of economic factors, food insecurity, anxiety towards COVID-19, job stability, and adherence to social distancing measures in determining mental health outcomes during the pandemic in Egypt. Additionally, it highlights the potential negative impacts of certain coping strategies on mental health, while identifying the most relevant predictors through its variable selection capability.

Table 5: Results of the elastic net regression of the factors predicting mental health scores

Variable	**Estimate**	**SE**	**t-value**	**p-value**
Intercept	18.76	0.49	37.94	0.0001***
Age	-0.021	0.01	-2.51	0.012**
Female	-0.39	0.19	-2.03	0.042**
Urban residents	-0.32	0.18	-1.75	0.079*
Education level				
Basic	-0.67	0.29	-2.28	0.022**
Secondary	0.08	0.19	0.401	0.687
Food insecurity				
Had difficulty purchasing the usual quantity due to price increases.	-0.67	0.21	-3.16	0.001***
Had difficulty purchasing the usual quantity due to decline income	-0.67	0.23	-2.85	0.004***
Had to reduce the usual amounts of food	-0.73	0.21	-3.38	0.0001***
Maintained the main job/activity during COVID-19 as before	0.79	0.27	2.93	0.003***
Income changes				
Stayed the same	0.44	0.21	2.07	0.038**
Increased by 1-25%	0.66	0.33	1.98	0.047**
Increased by more than 25%	0.82	0.73	1.17	0.264
Anxiety about being infected with COVID-19				
Rather worried	-0.68	0.24	-2.78	0.005***
Very worried	-0.78	0.23	-3.27	0.001***
I had it already	-1.41	0.51	-2.75	0.005***
Anxiety about economic situation				
little worried	-1.45	0.30	-4.81	0.0001***
Rather worried	-1.50	0.31	-4.92	0.0001***
very worried	-2.39	0.26	-9.03	0.0001***
Don’t wash hands with soap more often than before	-0.76	0.26	-2.87	0.004***
Aids from Takaful/Karama	0.46	0.35	1.31	0.188
Exceptional allowance for irregular worker	-0.56	0.54	-1.03	0.301
Support from NGO/CSO	1.33	1.12	1.18	0.235
Coping with the economic situation				
Spent savings	-0.44	0.19	-2.28	0.022**
Family/friends in country	-0.52	0.19	-2.70	0.006***
Borrowing bank/employer/lender	-0.46	0.26	-1.76	0.076*

Selling assets	-0.41	0.23	-1.79	0.072*
Goodness of fit test (F-test)				
F-value (df1 = 26; df2 = 3097)	16.37	p-value of F		0.0001***

Note: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. SE: standard error of estimate. df1: the degrees of freedom associated with the numerator in the F-ratio calculation; df2: the degrees of freedom associated with the denominator in the F-ratio calculation.

4.3 Comparison Between Three Penalized Regression Models

Based on the comparison table (Table 6), we can note the following on the performance of the ridge, LASSO, and elastic net regression models for predicting mental health scores during the COVID-19 pandemic in Egypt:

1. Adjusted R-squared: The elastic net model has the highest adjusted R-squared value (0.113469), indicating that it explains the most variation in the mental health scores compared to the other two models. The LASSO model has a slightly higher adjusted R-squared (0.112987) than the ridge regression model (0.110789).

Table 6: Comparison criteria between three penalized regression models

Criterion	**Penalized Regression Models**		
	Ridge	**LASSO**	**Elastic Net**
Adjusted R-squared	0.110789	0.112987	0.113469
SE	5.013581	5.007382	5.006019
AIC	18983.93	18963.36	18957.7
BIC	19256.04	19156.86	19127.01

2. Standard Error (SE): The elastic net model has the lowest standard error (5.006019), followed by the LASSO model (5.007382) and the ridge regression model (5.013581). A lower standard error indicates a better fit of the model to the data.

3. Akaike Information Criterion (AIC): The elastic net model has the lowest AIC value (18957.7), followed by the LASSO model (18963.36) and the ridge regression model (18983.93). A lower AIC value indicates a better trade-off between goodness of fit and model complexity, suggesting

that the elastic net model is the preferred model among the three.

4. Bayesian Information Criterion (BIC): Like the AIC, the elastic net model has the lowest BIC value (19127.01), followed by the LASSO model (19156.86) and the ridge regression model (19256.04). A lower BIC value also indicates a better trade-off between goodness of fit and model complexity, further reinforcing the superiority of the elastic net model.

Overall, based on the comparison metrics, the elastic net model emerges as the best-performing model among the three for predicting mental health scores during the COVID-19 pandemic in Egypt. It strikes a balance between handling multicollinearity (like ridge regression) and performing variable selection (like LASSO), while achieving the highest adjusted R-squared, lowest standard error, and lowest AIC and BIC values. These results suggest that the elastic net model provides the most accurate and parsimonious representation of the factors influencing mental health during the pandemic in this study.

5. DISCUSSION AND CONCLUSION

The study examined the repercussions of Coronavirus, including forms of food insecurity, changes in job activity, coping strategies for economic difficulties, and social distancing measures and their effects on individuals' well-being, using the latest data available for Egypt by the Economic Research Forum. The study also highlighted differences in individuals' mental health by sociodemographic characteristics, including gender, age, educational level, place of residence, and marital status, and investigated other key drivers of mental health outcomes during the pandemic. The current study showed that food insecurity, low household income, anxiety about the economic situation, and coping strategies for economic hardship were the primary drivers of mental health during the pandemic. In addition, some socio-demographic variables such as age, gender and place of residence played clear influences on mental health status during the pandemic.

As individuals age, their mental health scores tend to decline. This aligns with past research indicating that older adults, especially those retired, often adhere to stricter home-stay measures, like self-isolation and quarantine. Consequently, they experience heightened levels of stress,

anxiety, and depressive symptoms compared to their younger, employed counterparts [41]. Our research also suggests that mental health varies based on place of residence. Urban residents have poorer mental health than rural residents, which is likely related to how the pandemic has disrupted life and jobs in urban areas - with urban areas seeing a rise in job losses, reduced working hours, and lower wages. These factors contribute to increasing mental distress among city residents, as noted by Al-Zoghbi, who found that rural residents feel less psychological stress from the effects of the pandemic [5].

The study reveals that women are at a higher risk of mental health challenges compared to men. This finding aligns with prior studies highlighting that, amid the pandemic, women have disproportionately endured poor mental health status pandemic [3], [5], [32], [42], [43] Several factors predispose women to such vulnerabilities during these times. Mostly in developing nations, the disparity in domestic and caring duties is pronounced, with women shouldering most of these tasks independent of their partner's employment status—a situation exacerbated by the pandemic. The shutdown of educational institutions and childcare facilities has disrupted the routines of employed women, necessitating increase in their engagement with childcare and at-home education amidst the health crisis [6]. Moreover, women predominate in sectors that require high physical presence, which have suffered severely during the pandemic, further impacting their mental state [44].

COVID-19 has unleashed multiple stressors that impact individuals' mental health, particularly forms of food insecurity and financial losses. There is a direct relationship between food scarcity and poor mental health scores [45]. In addition, the pandemic-induced decline in household income has increased psychological distress in Arab countries [6], [43]. In line with previous studies, our study confirms the negative impact of food shortages and other forms of food insecurity as well as low household income on individuals' mental health. During the pandemic, a pattern has emerged revealing that people experiencing an increase in their household income tend to show improved mental health status compared to their counterparts experiencing a downward trend in their household income.

Coping strategies, such as selling assets and property, spending savings, resorting to borrowing, and asking for help from family and friends, also caused a deterioration in the psychological state of the individuals who adopted them during the pandemic period. On the other hand, assistance from government agencies, non-profit organizations, and other groups has failed to make a noticeable impact on individuals' mental health. Despite the best efforts of these actors, their support has not translated into significant improvements in the mental health scores of those they aimed to help.

After the emergence of the Coronavirus, individuals' expectations regarding personal income have changed. Amid continuing waves of uncertainty caused by the pandemic, a growing sense of economic vulnerability has taken hold among individuals. Our findings consistent with other studies revealed a stark correlation: those overwhelmed by severe concerns about the economic impact of COVID-19 reported poorer mental health status than their less anxious counterparts [8]. This pattern was reflected in mental health concerns about the risk of contracting the virus itself. In contrast, individuals who conscientiously practiced preventive measures such as social distancing and wearing masks showed stronger mental health than those who avoided such precautions.

Individuals experiencing various forms of food insecurity and low family income also need psychological support in addition to financial assistance. The government should pay special attention to vulnerable individuals who have coping strategies to deal with the negative impacts of the pandemic and improve their mental health by launching programs to promote wellness and enhance coping with the negative repercussions of the pandemic on their health and livelihoods. In addition, individuals who have experienced excessive anxiety about the economic situation and fear of contracting the virus should be integrated into psycho-education programs and other supportive interventions in such crises.

The study contributes to previous studies clarifying the negative effects of the epidemic on the mental health of individuals. Our findings can be relied upon to guide the distribution of aid to those affected by the pandemic. Importantly, women, urban dwellers, and less educated people

suffer from psychosocial distress and need targeted support. Furthermore, those experiencing food scarcity and low family income need mental health resources and financial support. The government must focus on helping these vulnerable groups who have severe coping strategies to deal with the negative through initiatives aimed at strengthening mental health and resilience in the face of the negative effects of the pandemic on their lives and well-being. In addition, those overcome by economic and virus-related concerns should be integrated into psycho-educational and supportive programs during such crises.

While the research provides valuable insights, it should be noted that its findings are drawn from a narrow demographic of mobile device users between the ages of 15 and 64. They commonly have higher education levels, are predominantly males, and enjoy greater income, which might skew the representativeness of the findings for the broader population. In addition, it's important to recognize that the study doesn't establish a causal relationship between the ramifications of COVID-19 and mental health conditions. Additionally, a significant gap in the data is the lack of pre-pandemic mental health records, raising concerns about potential pre-existing mental health problems or psychological treatments that could act as confounding variables in the analysis.

In future work, a modified penalized regression approach can be used to predict the mental health score in Egypt or apply this approach to another Arab country.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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