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**Determinants of Mental Health During the COVID-19 Pandemic in Egypt: A GSEM Analysis of Socioeconomic Factors and Income Changes Mediation**

**Abstract:** The COVID-19 pandemic, which emerged in late 2019, deeply impacted societies worldwide. Beyond its direct health outcomes, the pandemic brought about significant economic disruptions and triggered mental health challenges for many individuals. One area of consideration is the effect of income changes on mental health status. The Generalized Structural Equation Modeling (GSEM) model will identify the mediating impact of economic changes between the sociodemographic variables on mental health status in Egypt. The study indicated that changing income levels among the participants had a notable mediating impact on their mental health status during the COVID-19 pandemic. Additionally, factors such as total monthly income, employment status, primary occupation, concerns regarding the economic climate, educational attainment, household size, social support, and coping mechanisms significantly influenced changes in economic levels. Furthermore, aspects like the consequences of social distancing, place of residence, and fears of contracting the virus significantly impacted the mental health status of the population. Labor market variables were found to have a shared influence on both economic circumstances and mental health status. The GSEM model with the ordinal logistic regression equation was investigated to determine the direct effects of the independent variables on the economic status and the indirect effects of them on the mental health status in Egypt, according to the COVID-19 pandemic.

**Keywords:** COVID-19, Mental health, GSEM models, Mediating effect, Economic situation in Egypt.

1. **Introduction**

The global health crisis brought about by the COVID-19 pandemic has led to widespread ramifications and has led to profound social and economic repercussions. Increased unemployment and the changes in income levels were the major effects of this global pandemic. It was first in Wuhan City, China, on December 31, 2019. The World Health Organization declared the COVID-19 outbreak on March 11, 202 [1]. There are circumstances that the COVID-19 pandemic has caused an enormous amount of pressure and anxiety for numerous[2]. The relationship between economic and mental health status can be characterized as a recursive relation, where each factor can influence and be influenced by the other over time, and mental health status impacts economic outcomes[64], [34] , [65], [66]. Individuals experiencing mental health difficulties may face challenges in finding and maintaining employment, leading to reduced income and financial strain. Mental health issues can affect productivity, job performance, and interpersonal relationships, potentially resulting in job loss, decreased earning potential, and limited career advancement opportunities. Moreover, the costs associated with seeking treatment and managing mental health conditions can further exacerbate economic burdens.[3],[4] .Moreover, Economic factors, such as income, employment stability, and financial security, can impact an individual's mental health. Financial stress, income inequality, and job insecurity can contribute to heightened levels of anxiety, depression, and psychological distress. The economic challenges faced by individuals, such as unemployment or financial setbacks, can lead to emotions of hopelessness, diminished self-esteem, and a sense of loss of control, ultimately affecting mental well-being. These outcomes have been studied for decades[5] ,[6] ,[7]. Many studies have confirmed that unemployment and income changes impact mental health status and other elements of well-being.[8],[9],[10],[11],[12],[13] ,[14],[15].

The COVID-19 pandemic has caused large disruption in much of the global population, along many dimensions. The crisis has significantly worsened pre-existing socio-economic disparities, leading to a notable impact. the rates of morbidity and mortality increased simultaneously with the spreading of COVID-19 [16].

The fallout of the Coronavirus was applying social distancing and many restrictions on the population to limit the spread of the epidemic by closing schools, universities, coffee shops, restaurants, and malls.[17] The pandemic has also affected individuals and disrupted their stability through multiple channels, including job losses, reduced working hours, incomes, and increased prices for basic foods. Still, scant evidence exists on the effect of the COVID-19 pandemic on individuals' mental health [18].

The social distancing limitations may have led to social isolation, social restrictions imposed in response to the pandemic, and job losses from the economic downturn, all of which take their toll on people’s biological and mental health. The lockdown made job inquiries more difficult or impossible, and many employees lost their jobs[19].

Egypt grappled with an economic downturn caused by the COVID-19 pandemic, which prompted the implementation of various measures aimed at curbing the virus's transmission. These measures involved imposing restrictions on movement, prohibiting gatherings, and temporarily shutting down educational institutions and public spaces. Therefore, this study addresses a regional research gap by examining income as a mediator between socioeconomic factors and mental health during COVID-19 in Egypt to analyze the most effective factors on mental health, considering the economic changes. The Generalized Structural Equation Modeling (GSEM) framework extends the capabilities of traditional Structural Equation Modeling (SEM) by allowing for more flexibility in specifying the distribution of the outcome variable. The assumptions of the traditional Structural Equation Modeling (SEM) are violated, and the Generalized Structural Equation Modeling (GSEM) framework emerges as a versatile solution. GSEM becomes particularly suitable as the data for the nature of the data, the dependent variable (Mental health status is ordinal scale) and the independent variables are categorical, continuous, and ordinal moreover the mediating variable (income changing) is ordinal also, and more complex structural models that deviate from the linear, normally distributed assumptions of SEM. By accommodating a wider range of distributional assumptions and offering robust estimation methods, GSEM provides the study with a powerful tool to address violations of SEM assumptions. This flexibility allows for a more accurate representation of real-world data that may not conform to the strict assumptions of traditional SEM. GSEM is suitable here as it captures both direct and indirect effects within complex relationships. To analyze the effect of this economic crisis on the mental well-being of the Egyptian population during the pandemic, the Combined COVID-19 MENA Monitor Household Survey (CCMMHH) offers valuable data that can be utilized to analyze the connection between survey variables and changes in income levels as well as mental health status.

1. **Literature review**

An increasing number of researchers are analyzing how the COVID-19 pandemic is affecting mental health across various nations.

Abdelwahab et al. performed a study on the consequences of COVID-19 on workers' subjective well-being in four Middle Eastern and North African countries. They found that differences in the labor market due to the pandemic negatively impacted workers' well-being. The study emphasized the need for policies that decrease workers' vulnerability and support their livelihoods[20].

Daly et al. [21] analyzed the occurrence of mental health problems before and during the COVID-19 crisis in the UK. They found a significant increase in mental health issues during the pandemic, particularly among females, individuals with higher socioeconomic status, and young adults. However, some improvement was observed by late June 2020.

Giuntella et al. emphasized the large impact of COVID-19 on both lifestyle and well-being based on a longitudinal dataset from consecutive cohorts of young adults before and during the COVID-19 pandemic. Also, they linked biometric measures of physical activity and sleep to survey measures of mental well-being and social distancing. They also found a strong relationship between physical activity and mental health, with the pandemic mediating this relationship [22].

Xu et al. [23] examined the consequences of COVID-19 on mental health in the UK, revealing exacerbated disparities among groups with poorer mental health before the crisis. Women and younger individuals experienced more considerable growth in mental health crises compared to other demographic groupings.

Haque et al.[19] used a cross-sectional survey performed in June 2020 among 176 informal waste workers chosen from nine municipalities and one city corporation in Bangladesh. They used a single population proportion formula to select the required sample, the interview was conducted face-to-face. A General Health Questionnaire (GHQ-12) was used to assess respondents’ mental health. They discovered that a very high proportion of informal waste workers suffered from psychological distress during the COVID-19 pandemic. Factors, such as experiencing multiple COVID-19 symptoms by individuals and their family members, income reduction, and daily household meal reduction, are identified as contributing factors to poor mental health among waste workers.

Nkire et al. [24] investigated a cross-sectional survey with an online data collection survey on the impact of self-isolation or self-quarantine measures on self-reported stress, anxiety, and depression during the COVID-19 pandemic. They found a significant association between older age, employment status, and engaging in self-isolation or self-quarantine. More increased classes of stress and depression were reported by individuals practicing these preventive measures. Proto [25] compared pre- (2017-2019) and post-COVID-19 data (April 2020) for the same ethnic group of individuals within two waves of a cross-sectional and longitudinal study to evaluate and quantify differences in mental health among racial groups in the UK BAME (Black, Asian, and minority ethnic). They found a higher degeneration in mental health among men, BAME (Black, Asian, and minority ethnic), compared with British White individuals. However, for women, the degeneration in mental health is the same as for both BAME and British White individuals. The gender gap in mental health deterioration is significant among British White individuals and not significant among BAME individuals. Also, the decline in mental health among women and BAME men is very similar. The analysis of data also showed that people living in London and Scotland have suffered a worse decline in mental health compared to individuals living in England (excluding London), and self-employed and retired individuals have been more concerned than employed individuals. Finally, neither marital status nor household size predicts changes in mental health.

Adams-Prassl et al. [26] gathered real-time survey data on March and April 2020 of individuals in the United States to examine the impact of state-wide stay-at-home orders on mental health, which was selected to be representative in terms of region. They found a significant reduction in mental health among women, while the effect on men's mental health was insignificant. Dallas &Jones [27] analyzed data from Wave 9 of the UK Household Longitudinal Study (UKHLS) and the April 2020 Wave of the UKHLS COVID-19 survey to compare estimates of previous inequality of opportunity (IOP) in psychological distress, as estimated by the General Health Questionnaire (GHQ), before (Wave 9) and at the initial peak (April 2020) of the covid pandemic. They found a significant worsening of mental health and increased inequality of opportunity in psychological distress.

Etheridge & Spantig employed the Covid-19 module from the UK Household Longitudinal Survey (UKHLS), allocated monthly from April 2020, to show a substantial and statistically significant worsening of levels of psychological distress during the pandemic. They found a strong correlation between reductions in well-being and social factors. Moreover, reductions in well-being during the pandemic are extremely correlated with family responsibilities and financial circumstances. Also, with age, the young have been much more strongly affected than the old, as with that those aged between 16 and 30 years, both men and women, have been much more negatively affected than older individuals. Their result also registered an enormous drop after beginning, and is consistent with the existing evidence of an extreme effect on women. Similarly, they discover large declines in well-being reported by those in a tough financial situation. On the other hand, downfalls in well-being are not substantially larger for those reporting the loss of their jobs

Hayat et al[29]. examined the mental health status and associated factors among residents of Pakistan using an online questionnaire survey conducted from April 3 to May 7, 2020, using convenience and snowball sampling techniques. This study reported mild to moderate levels of depression, stress, and anxiety amidst the COVID-19 outbreak. Age, education, occupation, physical symptoms, and marital status have a significant impact on mental health during the COVID-19 pandemic

Bodenstein et al. [30] provided econometric proof that random social distancing was as expensive as required social distancing, using state-level data in the United States. They completed a study in Bangladesh to evaluate the mental health of university students during the COVID-19 lockdown. They observed 509 students and found that a significant number experienced imbalances in mental health, with 72.7% having moderate imbalances and 10.41% suffering from severe imbalances. Factors such as family members affected by COVID-19, insecurity, social media usage, and smoking habits contributed to these imbalances. On the other hand, being concerned about education, career, spending time with family, and participating in household chores decreased mental health disturbances. The study suggests implementing mental health plans and improving communication with family members to enhance the mental health of university students in Bangladesh.

Lelisho et al.[31]Performed a study in Southern Ethiopia to determine elements associated with generalized anxiety disorder (GAD) among mothers attending perinatal services during the COVID-19 pandemic. They set up 423 mothers using the GAD-7 scale and found that 31.7% had non/minimal to severe GAD. Elements associated with GAD included being a town resident, having an alcohol habit, having an occupation, being a healthcare worker, having a chronic illness, having a family history of anxiety or mood disorder, fear of contracting COVID-19, and level of perceived social support. The analysis recommends providing special awareness to mothers visiting perinatal services to ensure their mental health during the pandemic. Saraswathi et al. [32] aimed to investigate the impact of the COVID-19 pandemic on the mental health of undergraduate medical students. A group of 217 students from a medical college in Chennai, India, participated in a longitudinal study. The researchers assessed levels of depression, anxiety, and stress before and during the COVID-19 outbreak using the Depression Anxiety Stress Scale 21 Items (DASS-21). They also examined sleep quality and the students' experiences with COVID-19-related stressors through self-administered questionnaires. The results indicated a significant increase in anxiety and stress levels during the pandemic, while depression symptoms remained unchanged. Factors such as poor sleep quality, higher baseline levels of depression, anxiety, and stress, COVID-19-related worries, having COVID-19 patients among family or friends, and direct interactions with COVID-19 patients were identified as significant predictors of negative mental health outcomes. The study emphasizes the importance of addressing and mitigating the adverse effects of the COVID-19 pandemic on the mental well-being of undergraduate medical students. Strategies such as providing resources for stress management, promoting healthy sleep patterns, and addressing COVID-19-related concerns are crucial in supporting the mental health of this vulnerable population.

Bartik et al. [33] analyzed the consequences of COVID-19 on small businesses in the United States. They observed over 5,800 small businesses and compared the data with the 2017 Census of US Businesses. The study found that many discharges and closures happened within an irregular week of the crisis, indicating the financial vulnerability of many small businesses. Most businesses are scheduled to seek funding through the CARES Act, a government response to keep businesses open during the pandemic.

Béland et al[34] studied the short-term outcomes of COVID-19 on jobs and salaries in the United States. They used data on COVID-19 cases and jobs from the Current Population Survey (CPS). The study demonstrated that COVID-19 raised the unemployment rate, reduced hours of work and labor force participation, and had no significant effect on wages. The effects were particularly pronounced for seasonal workers and disproportionately affected men, younger workers, Hispanics, and less-educated workers.

Cajner et al. [35] examined the detailed differences in the U.S. labor market during the early months of the pandemic. They used weekly administrative data from ADP, a provider of human resources services, to analyze job trends by worker characteristics such as age, gender, initial wage levels, and worker residence state. The study found that employment collapsed from mid-February to late April, with a 21% decline compared to early February. Krafft et al. [36] studied the impact of    COVID-19 on labor markets in the Middle East and North Africa (MENA) region. They used data from the ERF COVID-19 MENA monitor surveys and examined labor force participation, employment, unemployment, and transitions among different worker categories. The analysis found a slight increase in employment rates and labor force participation, along with reduced unemployment rates. However, wage workers, farmers, and the self-employed faced different challenges, including ongoing layoffs and decreased earnings.

Habtewold [37] conducted a study in Ethiopia to examine the impacts of COVID-19 on food security, employment, and education. Using data collected by the World Bank through phone calls, the study found that COVID-19 adversely affected food security, employment, and schooling. The impacts varied among different household groups, and certain restrictions had a more significant effect on welfare. The study highlighted the adverse influence of the pandemic on business operations and employment conditions in Ethiopia.

Antipova [38] examined the impact of the pandemic-induced economic recession on vulnerable communities and found that marginalized regions suffered greater economic damage. The study focused on COVID-19-related labor market outcomes, particularly employment and unemployment rates among socially disadvantaged groups.

Bryan et al. [39] investigated the effects of COVID-19 on disabled individuals in the UK workforce. It was discovered that disabled individuals experienced more significant reductions in working hours and higher rates of temporary work absence compared to non-disabled individuals. Accessing healthcare, personal assistance, and community networks posed challenges for disabled people during the pandemic.

Breisinger et al. [40] introduced that in the second quarter of 2020, working hours decreased by 16.9 percent in the Arab States, resulting in significant losses in labor income. This decline also led to the loss of over 10 million full-time employment positions in the Middle East and North Africa (MENA) region. In response to the negative impacts on well-being resulting from job and income losses, individuals have employed various coping strategies.

Suleiman [41] Suleiman proved that in Egypt, a significant portion of the population has been heavily impacted by the crisis. Specifically, among the individuals most affected, 55.7 percent are experiencing a reduction in working hours or days, 18.1 percent are engaged in irregular work patterns, and 26.2 percent have become unemployed. These individuals have adopted various strategies to mitigate the negative effects on their well-being.

Abdel-Rahman et al.[42]concentrated on the reduction of women's employment levels across five Arab nations during the COVID-19 pandemic. It found that women with caregiving duties faced higher risks of losing their jobs, whereas those employed in the public sector and possessing health insurance experienced greater job security. Telecommuting emerged as a vital factor in enabling women to maintain their employment status. Abdel-Rahman et al.[43] assessed the gender disparity in labor market impacts amid the COVID-19 crisis in five MENA countries. Women were identified as more vulnerable to adverse job consequences, such as permanent job displacement and alterations in their primary occupations. The increased demand for childcare and household responsibilities significantly affected women's labor market outcomes.

Thang DAO et al[44]investigated the impact of the COVID-19 pandemic on the income of service workers in Vietnam. Various factors, including education level, work area, job creation activities, cost of living, and investment, contribute to an individual's income. It revealed significant income disparities based on work area and gender, with an overall decrease in wages following the outbreak. Public sector workers generally earned more than their private sector counterparts.

Radulescu et al. [44]examined the impact of the ongoing global crisis, specifically the COVID-19 pandemic, on the labor market in Romania. Due to the limited information available regarding the pandemic and its effects, a questionnaire was administered to the population to gather research findings. The pandemic increased unemployment rates, but respondents reported improved outcomes and maintained similar incomes. Participants emphasized the importance of preventive measures and comprehensive health insurance when considering job changes.

Elbehairy et al. [45] examined the impact of the COVID-19 pandemic on labor market outcomes in Egypt, Jordan, Tunisia, and Morocco, focusing on gender differences. The study found a decrease in employment and an increase in unemployment, with higher rates for women, particularly in the private-wage employment sector.

Abdel-Rahman et al. [46] utilized data from the COVID-19 MENA Monitor Household Survey conducted by the Economic Research Forum, focusing on Egypt. The survey was conducted via phone in two waves, in February 2021 and June 2021, with a total of 4,007 respondents aged 18-64 who are mobile phone owners. The individuals' mental health during the pandemic was assessed using the 5-item World Health Organization Well-Being Index (WHO-5). Penalized regression models were employed to identify the key drivers of mental health status. They found that women, middle-aged adults, urban residents, and individuals from low-income households were at higher risk of poor mental health. Factors such as food insecurity, reduced household income, stress about financial status, and concerns about contracting the virus negatively impacted mental health.

Akbulaev et al.[47] examined the economic effect of COVID-19, discussing the methods of investigating the infection, the virus's history and development, and its impact on countries and employment opportunities.

Almeida et al. evaluated the implications of the COVID-19 crisis on household salaries in the European Union (EU). The study found that the pandemic negatively affected disposable income, particularly for lower-income households. However, discretionary fiscal policies implemented by EU Member States helped mitigate the impact, similar to the 2008-2009 financial crisis.[48]

Aylin Bayar et al. [48] developed a heuristic method to estimate the effects of the COVID-19 pandemic on jobs, inequality, and poverty in Turkey. The study generated various scenarios using data from the 2017 Survey of Income and Living Conditions. The findings suggest that the pandemic is expected to lead to a significant increase in unemployment, as well as higher levels of inequality and poverty in the country.

Yabe et al. [49] analyzed the changes in the observations of income variety in urban encounters during the COVID-19 pandemic. The study utilized a large-scale dataset of over one million anonymized mobile phone users in Boston, Dallas, Los Angeles, and Seattle. The results indicate a substantial decrease (ranging from 15% to 30%) in the diversity of urban encounters during the pandemic. This decline persisted even after mobility metrics returned to pre-pandemic levels. The study attributes the decrease in encounter diversity to behavioral changes, such as reduced willingness to explore new places. These findings have implications for managing the balance between COVID-19 procedures and the variety of urban encounters as societies transition exceeding the pandemic.

Li et al. [50] conducted a real-time analysis of the COVID-19 crisis's effects on income distribution in Australia. The study combined data from multiple sources, including surveys and administrative payroll data, using a semi-parametric approach. The analysis covered the period between February and June 2020, encompassing the initial outbreak of COVID-19. Despite an increase in unemployment, the study found a decrease in income inequality during this period. The implementation of additional wage subsidies and welfare support as part of the policy response effectively offset the increase in income inequality caused by the income shock effect. However, the study raises concerns about the potential reversal of these changes once the support measures are withdrawn, suggesting a possibility of worsening income inequality and living standards.

Beland et al. [51] investigated the immediate impacts of COVID-19 and stay-at-home directives on employment and salaries in the United States. It was discovered that COVID-19 resulted in a rise in joblessness, a reduction in working hours, and a fall in workforce engagement, especially among younger, non-white, single, and less-educated employees. Individuals with the ability to telecommute were at lower risk of facing adverse labor market outcomes, whereas those working closely with colleagues were disproportionately impacted. Furthermore, the research underscored that stay-at-home orders lowered instances of COVID-19 infections and fatalities but brought about economic repercussions like income loss and diminished tax.

Bundervoet et al. [52] investigated the short-term effects of the COVID-19 pandemic on households in developing countries using data from 31 countries. The study found that a significant percentage of respondents experienced job and income losses, particularly among vulnerable groups such as women, youth, individuals with lower education levels, self-employed workers, and casual workers. The impacts of the pandemic were regressive and also led to disruptions in education, especially for children from lower-income countries and households with less-educated parents in rural areas. The study emphasized the need for inclusive recovery policies and resilience-building to address the risk of increased inequality. Recent shards of evidence show that COVID-19 will have nontrivial effects on the international economies. A proportional intervention is desired from policymakers to balance the advantageous consequences of strong controlling activities in the health sector versus the potential economic and social consequences of those actions.

Wilkinson et al [53]discuss the challenges and considerations in addressing COVID-19 in informal settlements. The paper highlights the vulnerabilities and limited access to water and sanitation in these densely populated areas, making traditional preventive measures difficult to implement. It suggests the importance of balancing public health interventions with social and economic interventions, particularly regarding the informal economy that many urban poor rely on. The paper emphasizes the need for collaboration, coordination, and investment in improved data for monitoring the response in informal settlements.

Giovanis et al.[54] focus on the subjective well-being (SWB) of individuals who have experienced earning losses due to the COVID-19 pandemic and have adopted coping strategies. The study examines the perception of the economic situation and mental well-being and estimates the well-being costs associated with these coping strategies. The research utilizes ERF COVID-19 MENA Monitor Surveys conducted in Egypt, Jordan, Morocco, and Tunisia. Moreover, A lot of studies focused on the COVID-19 effect on mental health. [55],[56].[57].[58].

After a review of the literature, we can say that the main objective of our study is examining the mediating role of income changes in the relationship between socioeconomic factors and mental health during COVID-19 in Egypt using GSEM analysis. This paper proceeds as follows. We describe the data and methodology in Section 3. In Section 4, the empirical study was shown which contains the descriptive statistics and estimating the mediating variable and the result of the GSEM model. Section 5 includes the conclusion.

1. **Data and methodology**

The study primarily utilized the Combined COVID-19 MENA Monitor Household Survey (CCMMHH), administered by the Economic Research Forum (ERF). This survey involved telephone interviews with a nationally representative sample of mobile users aged 18-64, offering standardized data for Arab nations. It delved into various aspects including the pandemic's effects on employment, income levels, mental well-being, food security, coping mechanisms, adherence to social distancing measures, as well as changes in employment and income. This study investigated the collected data for Egypt on waves two and four.[59]

The survey meticulously gathered data on participants' mental health statuses, pinpointing adverse shifts in their financial situations, employment statuses, and psychological well-being. Specifically focusing on Egypt during waves two and four, the study used the WHO-5 brief questionnaire to assess mental health. This questionnaire comprises five inquiries emphasizing positive mental states, with respondents rating the frequency of feeling cheerful, calm, energetic, refreshed, and engaged in their daily activities over the prior two weeks. Responses were graded from 0 to 5 on a Likert scale, with higher scores indicating better subjective mental health. The survey responses were amalgamated to form an overall evaluation of mental well-being. The WHO-5 questionnaire, with Cronbach’s alpha coefficient of 0.702, was deemed reliable. Through explanatory factor analysis, the data was quantified and categorized into an ordinal scale using predefined thresholds.

Structural equation modeling attempts to estimate the value and significance of the relationships between a series of variables (independent and mediator) and the direct and indirect relationship between them, as well as the extent of the impact of these variables on the dependent variable. It is considered one of the multivariate analysis models, allowing for multiple dependent variables, it is an extension of multiple linear regression models. The independent variables, maybe continuous or categorical. Also, it deals with two types of measured variables: the observed and latent variables.[60]

Structural equation modeling is a comprehensive extension of the general linear model, enabling the simultaneous examination of a series of regression equations. However, in line with the specific model under investigation, the mediator and dependent variables were measured on an ordinal scale. At the same time, the latter was assessed implicitly based on a predefined set of expressions. Furthermore, the independent variables exhibited diverse levels of measurement, encompassing categorical, ordinal, and continuous scales, with some variables assessed implicitly. Consequently, the model was constructed, and its validity was assessed using STATA ver18, which facilitated evaluating the model's goodness of fit and reliability.

However, given the nature of the current model, the measurement levels and types of variables, especially the mediating and dependent variables, differ. The mediating variable is ordinal income change, and the dependent variable mental health is ordinal. Additionally, the relationship between exogenous variables may be either binary, categorical, continuous, or ordinal, while the mediating variable (ordinal, requires that the direction of the relationship is represented by an arrow from the exogenous variable to the mediating variable. This indicates a relationship between two continuous or binary variables, or one continuous and the other binary. Thus, we face either a binary logistic regression model, a linear regression model, or an ordinal logistic regression model. Consequently, reliance was placed on the Generalized Structural Equation Modeling (GSEM), which is a feature of the STATA statistical package that deals with SEM in the absence of a linear relationship between the variables.

1. **Empirical study**

Table (1) provides a comprehensive overview of the study variables and their significant relationships with mental health outcomes. Key findings indicate that gender, residence (urban vs. rural), marital status, main work type, worry about the economic situation, employment status, income change, past month's social support, and coping strategies all show significant associations with mental health. These results suggest that socio-demographic factors, economic concerns, and employment status play crucial roles in determining mental well-being within the study population. Interestingly, governmental support, age, educational level, governmental support, Number of children under six years, and social distancing practices do not exhibit significant relationships with mental health.

**Table (1) The characteristics of the study variables.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Frequencies and percentages | | | The statistic and significance |
| Gender | | Male | 2545(63.5%) | T=-5.525\*\*\* |
| Female | 1462(36.5%) |
| Age | Mean =35.15 year | | | R=0.027 |
| Residence | Urban | | 2077(51.8%) | T= 2.879\*\*\* |
| Rural | | 1930(48.2%) |
| Education | | Less than basic | 687(17.1%) | F=1.81 |
| Basic | 507(12.7%) |
| Secondary | 1866(46.6%) |
| Higher education | 947(23.6%) |
| Marital status | Never Married | | 963(24%) | 5.625\*\*\* |
| Currently Married | | 2866(71.5%) |
| Widowed/divorced | | 178(4.4%) |
| Main work | Farmer | | 63(1.6%) | 4.100\*\*\* |
| Firm owner | | 518(12.9%) |
| Unpaid household worker on a farm | | 7(.2%) |
| Unpaid household worker (but not a farmer) | | 5(.1%) |
| Pay workers for the Government / public sector | | 467(11.7%) |
| Pay Workers for a private sector /NGO | | 1382(34.5%) |
| Jobless and looking for work | | 202(5%) |
| Housewife | | 946(23.6%) |
| Full-Time Student | | 260(6.5%) |
| Quit | | 73(1.8%) |
| Otherwise | | 84(2.1%) |
| Number of children under six years | Mean= 0.5 | | | R=- 0.011 |
| Household size | Mean=4.74 | | | R=0.033\*\*\* |
| Total income | Less than 1750 EGP | | 1197(29.9%) | F= 14.565\*\*\* |
| 1750- less than 2500 EGB | | 1085(27.1%) |
| 2500-less than 4000 EGP | | 938(23.4%) |
| 4000 or more | | 454(11.3%) |
| I don't know | | 270(6.7%) |
| Refused (Don't read) | | 63(1.6%) |
| Worrying about the economic situation | Not at all worried | | 795(19.8%) | F= 78.830\*\*\* |
| Slightly worried | | 666(16.6%) |
| Fairly worried | | 774(19.3%) |
| Extremely worried | | 1772(44.2%) |
| Worrying from infection | Not at all worried | | 1428(35.6%) | F=21.539\*\*\* |
| Slightly worried | | 608(20.3%) |
| Fairly worried | | 812(20.3%) |
| Extremely worried | | 1024(25.6%) |
| I had the virus | | 135(3.4%) |
| Employment | Not employed | | 1679(41.9%) | T=-4.508\*\*\* |
| Employed | | 2328(58.1%) |
| Income change (The mediator) | Reduced by more than 25% | | 923(23%) | F=28.818\*\*\* |
| Reduced by 1-25% | | 925(23.1%) |
| Stayed the same | | 1763(44%) |
| Raised by 1-25% | | 341(8.5%) |
| Raised by more than 25% | | 55(1.4%) |
| Regular government support | Not Mentioned | | 909 (22.7%) | T=.500 |
| Mentioned | | 3098 (77.3%) |
| Past month's governmental support | Not Mentioned | | 3764 (93.9%) | T=.609 |
| Mentioned | | 243(6.1%) |
| Past month's social support | Not Mentioned | | 3684(91.9%) | T=-2.301\*\*\* |
| Mentioned | | 323(8.1%) |
| Coping strategies | Not Mentioned | | 2318(57.8%) | T =-7.273\*\*\* |
| Mentioned | | 1689(42.2%) |
| Social distancing | Yes | | 2919 (72.8%) | T =-.990 |
| No | | 1088 (27.2%) |

Due to the COVID-19 pandemic, numerous workers lost their jobs and income resources, and others suffered from decreased working hours and pay delays [61] [62]. Moreover, there was an extreme and quick drop in mental health in many countries worldwide.

* 1. **The result of the GSEM Model**

The sample size included in the analysis was 4007 cases, and the Log Likelihood function value was -10171.273. As mentioned, the dependent variable used was "mental health," which was considered an indicator of the mental health status for the observation. This variable takes four ordinal values: either 1 if the case at most and more than half of the time feeling good mental health, value two if the cases feeling good less than half of the time, and three if the cases having good mental health status at some of the time, the fourth category to the people who have bad mental health status. Therefore, according to the ordinal logistic regression model, which includes an ordinal dependent variable, there are three cut-off points: the first at -.3635218, the second at .8573921, and the third at 2.818705.

Table (2) The variables code in the study

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable name** | **Variable code** | **Variable name** | **Variable code** |
| Worrying from infection | X10 | Sex | X1 |
| Worrying about economic situations | X11 | Age | X2 |
| Employment | X12 | Residence | X3 |
| Regular governmental support | X13 | Education level | X4 |
| Past month's governmental support | X14 | Marital status | X5 |
| Past month's social support | X15 | Main work | X6 |
| Coping strategies | X16 | Number of children under the age of six | X7 |
| Social distancing | X17 | Household size | X8 |
| Income changes among COVID-19 pandemic | Z | Total income | X9 |
| Mental health status of the observations among COVID-19 pandemic in Egypt. | | | Y |

* 1. **Estimating the mediator variable (Income change)**

As mentioned in the previous section, the model comprises a set of external variables. Since we are constructing a model for structural equations, it is necessary to clarify the structural equations for each variable in the model.

The mediator variable (income changes) estimated ordinary take 5 categories from 1 to 5,1 when then income decreased by more than 25%, 2 when the income decreased by 1-25%, 3 when the income Stayed the same, 4 when the income increased by 1-25%, and 5 when the income increased by more than 25%. The nature of the income change is an ordinal scale, so the ordinal logistic regression (OLR) equation was used to estimate the probability. The variable has four so, it has four cuts of points as follows (0.187325, 1.324802, 3.849335, and 5.938).

The first cut-off point distinguishes between the first category (when the income decreased by more than 25%), the second category (when the income decreased by 1-25%), and the third category (when the income Stayed the same). The value of the cut-off point 0.187325 means that observations (according to the characteristics of the explanatory variables when they equal zero) with a value of 0.187325 or less will be classified as belonging to the first category when the values of the explanatory variables are equal to zero. On the other hand, the second cut-off point distinguishes the first and second categories from the third category. The value of the cut-off point 1.324802 means that observations - according to the characteristics when they equal zero - with values greater than 1.324802 will be classified as belonging to the third category when the values of the explanatory variables are equal to zero. Observations with values between -.187325 and 1.324802 will be classified as belonging to the second category. The same goes for the third and fourth cuts of points.

Table (3) The coefficient of exogenous variables on the mediating variable

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **coefficient** | **Std error** | **Z** | **P** | **95% conf. interval** | |
| x10 | 0.044468 | 0.025346 | 1.75 | 0.079 | -0.00521 | 0.094144 |
| x9 | 0.081528 | 0.024467 | 3.33 | 0.001 | 0.033574 | 0.129481 |
| x4 | 0.160037 | 0.031249 | 5.12 | 0.000 | 0.09879 | 0.221285 |
| x5 | 0.017263 | 0.076659 | 0.23 | 0.822 | -0.13298 | 0.167511 |
| x11 | -0.19615 | 0.027269 | -7.19 | 0.000 | -0.24959 | -0.1427 |
| x12 | 0.719921 | 0.079366 | 9.07 | 0.000 | 0.564365 | 0.875476 |
| x1 | -0.07061 | 0.079412 | -0.89 | 0.374 | -0.22625 | 0.085038 |
| x6 | 0.169756 | 0.016237 | 10.45 | 0.000 | 0.137932 | 0.20158 |
| x8 | -0.0416 | 0.016511 | -2.52 | 0.012 | -0.07396 | -0.00924 |
| x7 | 0.006794 | 0.036711 | 0.19 | 0.853 | -0.06516 | 0.078745 |
| x2 | 0.003558 | 0.003307 | 1.08 | 0.282 | -0.00292 | 0.010039 |
| x13 | 0.045532 | 0.072383 | 0.63 | 0.529 | -0.09634 | 0.1874 |
| x14 | -0.18717 | 0.122861 | -1.52 | 0.128 | -0.42798 | 0.053632 |
| x15 | -0.62401 | 0.109747 | -5.69 | 0.000 | -0.83911 | -0.40891 |
| x16 | -0.37783 | 0.061198 | -6.17 | 0.000 | -0.49778 | -0.25789 |
| x17 | 0.054674 | 0.068465 | 0.8 | 0.425 | -0.07952 | 0.188863 |
| x3 | 0.05102 | 0.061393 | 0.83 | 0.406 | -0.06931 | 0.171348 |

(Source: researchers from STATA output)

The previous table (3) determined the significant effect of the exogenous variables on the mediating variable (the income changes). Variables of total income, educational level, worry from the economic situation during the COVID-19 pandemic, employment, main job, household size, past month's social support, and coping strategies have statistically significant p-values indicating their strong impact on changing the case's income.

Table (4) cuts off points of the mediator variable and the probability for each category.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Z=5 | Z=4 | Z=3 | Z=2 | Z=1 | **Mediator categories** |
|  | 5.938 | 3.849335 | 1.324802 | .187325 | **Cut off points** |
|  | \*\*\* | \*\*\* | \*\*\* | \*\*\* | **Significance** |
| .002678 | .018542 | .191799 | .244745 | .542235902 | **Probability** |

(Source: STATA output, \*\*\* referring to the significance of 95% CI)

The probability on the previous table of the mediator variable was estimated based on the values of the significant independent variables table (4) (wherein the equation, the quantitative external variable was compensated for by the mean, and the categorical variable was compensated for by the value zero or one referring to (the first category) In the following points, we will present the equations for estimating the mediator variable included in the model. The following equations represent the probability of the categories for the mediator variable.

* 1. **Estimating the marginal probabilities of the dependent variable (mental health status):**

The nature of the dependent variable is ordinally taking four categories, 1 when the observations feel good at most and more than half of the time, 2 when they feel good mental health status less than half of the time, 3 when the observations feel good some of the time and 4 when they don’t feel good mental health status. Using the ordinal logistic regression equation to calculate the probability of the significant variables on the dependent variable.

We constructed a structural equation model for the data in the previous section. As observed, the model consisted of three levels of variables: exogenous variables, the mediating variable, and the dependent variable. The values of the mediating variable were estimated based on the ordinal level.

Table (5) The coefficient of variables on the dependent variable

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **coefficient** | **Std error** | **Z** | **P** | **95% conf. interval** | |
| Z | -0.22089 | 0.031366 | -7.04 | 0.000 | -0.28237 | -0.15942 |
| x10 | 0.116602 | 0.024918 | 4.68 | 0.000 | 0.067764 | 0.165439 |
| x9 | -0.12471 | 0.024136 | -5.17 | 0.000 | -0.17201 | -0.0774 |
| x4 | 0.064856 | 0.031008 | 2.09 | 0.036 | 0.004082 | 0.125629 |
| x5 | 0.00079 | 0.075645 | 0.01 | 0.992 | -0.14747 | 0.149051 |
| x11 | 0.231189 | 0.027316 | 8.46 | 0.000 | 0.17765 | 0.284728 |
| x12 | -0.07259 | 0.076569 | -0.95 | 0.343 | -0.22266 | 0.077485 |
| x1 | 0.058497 | 0.077565 | 0.75 | 0.451 | -0.09353 | 0.210521 |
| x6 | -0.00698 | 0.015931 | -0.44 | 0.661 | -0.03821 | 0.024241 |
| x8 | 0.031205 | 0.016557 | 1.88 | 0.059 | -0.00125 | 0.063657 |
| x7 | -0.02736 | 0.036199 | -0.76 | 0.45 | -0.09831 | 0.043584 |
| x2 | 0.013728 | 0.003297 | 4.16 | 0.000 | 0.007266 | 0.02019 |
| x13 | -0.04923 | 0.071505 | -0.69 | 0.491 | -0.18938 | 0.090915 |
| x14 | -0.16635 | 0.120584 | -1.38 | 0.168 | -0.40269 | 0.069995 |
| x15 | 0.014211 | 0.107642 | 0.13 | 0.895 | -0.19676 | 0.225186 |
| x16 | 0.281095 | 0.060025 | 4.68 | 0.000 | 0.163448 | 0.398742 |
| x17 | 0.332196 | 0.067654 | 4.91 | 0.000 | 0.199596 | 0.464796 |
| x3 | -0.18868 | 0.060427 | -3.12 | 0.002 | -0.30711 | -0.07024 |

(source: researcher from Stata output)

From the previous table (5), the variables income change (z), worrying from infection, age, coping strategies, social distancing, residence, total income, educational level, and worry about economic situations have a significant effect on mental health status during the COVID-19 pandemic in Egypt with a 95% confidence level Figures from (1-8)

In this part, we will discuss the direct impact of the significant exogenous variables on the dependent variable (the mental health status in Egypt), which is ordinal. According to this nature, the model between each exogenous variable and the dependent variable is an ordinal logistic regression with three cut-off points. Since the dependent variable has four categories, Table (6) below illustrates the cut-off points for the dependent variable. The first cut-off point distinguishes between the first category (the case at most and more than half of the time feeling good mental health), the second category (the cases feeling good at less than half of the time), and the third category (the cases having good mental health status at some of the time) and, the fourth category to the people who have bad mental health status. The value of the first cut-off point, -.3635218, indicates that the case (based on the explanatory variable properties when equal to zero) with a value of -.3635218 or lower will be classified as belonging to the first category when the values of the explanatory variables are equal to zero. The table also shows the mental health status probabilities for the three categories of the dependent variable and the significance level for each category. The results in the table all showed significance at a significance level of 0.05.

The marginal probabilities in table (6) of the dependent variable were estimated based on the values of the significant independent variables in table (5) (wherein the equation of the ordinal logistic regression, the quantitative external variable was compensated for by its mean, and the categorical variable was compensated for by the value of the last category. The following equations represent the probability of the categories for the dependent variable.

Table (6) The cut-off points of the dependent variable.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Y=1** | **Y=2** | **Y=3** | **Y=4** |
| **Cuts** | -0.3635218 | 0.857392 | 2.818705 |  |
| **Probability of mental health status** | .3651485 | 0.29596 | 0.28808 | 0.073917 |
| **Significant level** | \*\*\* | \*\*\* | \*\*\* | \*\*\* |
| **Total effect** | .32641932 | .295214 | .299497 | .07887 |

(\*\*\* referring to the significance of 95% CI)

The marginal probability of the variables is calculated by changing the arbitrary values for the quantitative variables by increasing the mean by one and for categorical variables by changing the variable value to the next category the result is shown in the next table.

Table (7) The marginal probability of the variables on the different levels of the dependent variable (mental health).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **The change of Y** | P(y=1|xi) | P(y=2|xi) | P(y=3|xi) | P(y=4|xi) |
| income change (z) | .441770660 | 0.295282 | 0.298764 | 0.078543 |
| Worrying from infection | 0.301318642 | 0.292526852 | 0.331170538 | 0.074983969 |
| Age | 0.323408214 | 0.294991001 | 0.313447593 | 0.068153192 |
| Coping strategies | 0.28594863 | 0.284973 | 0.333463 | 0.095615 |
| social distancing | 0.151302077 | 0.369518319 | 0.38085506 | 0.098324544 |
| Residence | 0.36917687 | 0.29571303 | 0.278740977 | 0.056369123 |
| Total income | 0.354408175 | 0.324071 | 0.308094 | 0.013427 |
| Educational level | 0.312323101 | 0.279844 | 0.294654 | 0.113179 |
| Worry about economic situations | 0.27775719 | 0.239519 | 0.28098 | 0.201743 |

(Source: STATA output)

* 1. **The marginal probability of the income changes on the mental health status in Egypt according to the COVID-19 pandemic:**

The mediating variable (income change across the COVID-19 pandemic) as mentioned is an ordinal variable. The results indicate that when an increase follows the income increase in the probability that the case belongs to the first category of the dependent variable) from .32641932 to .441770660, an increase of 5.255%, with all other external variables held constant. This means that cases whose income changes become less (increasing their income) are more likely to have good mental health status compared to those mentioned.

* 1. **The marginal probability of being worried about infection with the COVID-19 virus on the mental health status in Egypt:**

The variable of being worried about infection with the COVID-19 virus is considered an ordinal variable, taking the values from 1 to 5, 1 if the cases are not at all worried, 2 if the cases are A slightly worried, 3 Fairly worried, 4 when cases are extremely, and 5 when cases had already infected. The analysis result indicates that transitioning to be more worried followed by a decrease in the probability that the case belonging to the first category of the dependent variable from 0.32641932 to 0.301318642, a 2.510067802% reduction, with all other external variables held constant. Similarly, in the second category of the dependent variable. This means that cases who are less worried are more likely to have good mental health status compared to those mentioned.

* 1. **The marginal probability of the age per year on the mental health status in Egypt according to the COVID-19 pandemic:**

Increase in the average age of the case by one year, the probability of belonging to the first category of the dependent variable (feeling good mentally at most and more than half of the time) will decrease from .3651485 to 0.323408214, a decrease of .0.301110553%, with all other external variables remaining constant.

* 1. **The marginal probability of coping strategies on the mental health status according to the COVID-19 pandemic in Egypt:**

The variable of coping strategies is considered a binary external variable, taking the value 0 if the cases are not mentioned in the coping strategies and 1 if they are mentioned. The analysis result indicates that transitioning from not mentioned to be mentioned is followed by a decrease in the probability that the case belonging to the first category of the dependent variable from 0.32641932 to 0.285948, a decrease of 7.919992%, with all other external variables held constant. This means that not-mentioned cases are more likely to have good mental health status compared to those mentioned. Regarding the probability of belonging to the second, third, and fourth categories of the dependent variable, transitioning from not mentioned to be mentioned to the coping strategies increases the probability of being in the categories with (1.367&,4.55858%, and 1.99349 successively) which mean the mentioned cases are more likely to have bad mental health status, with all other external variables held constant.

* 1. **The marginal probability of social distancing on the mental health status according to the COVID-19 pandemic in Egypt:**

The variable of social distancing is considered a binary external variable, taking the value 0 for cases that are dedicated to social distancing and 1 for those who aren't dedicated cases. The analysis result indicates that transitioning from being dedicated to not dedicated followed by a decrease in the probability that the case belonging to the first category of the dependent variable from 0.32641932 to 0.151302077, a decrease of 17.51172425%, with all other external variables held constant. This means that cases who are dedicated to social distancing are more likely to have good mental health status compared to those not mentioned.

* 1. **The marginal probability of residence on the mental health status in Egypt:**

Residence is considered a binary external variable, taking 1 for urban cases and 2 for rural. The analysis result indicates that transitioning from urban to rural is followed by an increase in the probability that the case belonging to the first category of the dependent variable from 0.32641932 to 0.36917687, an of 4.279%, with all other external variables held constant.

* 1. **The marginal probability of total income on the mental health status in Egypt:**

Total income is an ordinal variable as the category increases the total income increases also. The results indicate that when the total income increases the probability that the case belongs to the first category of the dependent variable) increase from 0.32641932 to 0.354408175, an increase of 2.798885506%, with all other external variables fixed. This means when the total income was increased the cases are more likely to be in a good mental health status.

* 1. **The marginal probability of educational level on the mental health status in Egypt:**

Educational level is an ordinal variable as the category increases the total income increases also.

Start with category 1 referring to less than basic, 2 for basic, 3 for secondary school, and 4 for higher education. The results indicate that on the higher educational level the probability that the case belongs to the first category of the dependent variable) decrease from 0.32641932 to 0.312323101, an increase of 1.40962182%, with all other external variables fixed. This means when the case has a lower level of education this led to an increase in the probability of having a good mental health status in Egypt.

* 1. **The marginal probability of worrying about the economic situation on the mental health status in Egypt:**

Worrying about the economic situation is an ordinal variable increasing its values means that the case will be more worried about the economic situation in Egypt according to the COVID-19 pandemic. The analysis result refers to being more worried about the economic situation decreasing the probability of being in the first category of the dependent variable (having good mental health status) from 0.32641932 to 0.27775719 with a 4.866212972% decrease.

In general, with respect to mental health status categories. When people feel good mental health for most of their day and more than half of the time, their income changes and commitment to the implications of social distancing have the greatest influence among the other variables in the study. However, Age and Educational level have the least effect on changing their mental status as shown in Figure (9).

For people whose feel-good mental health status is less than half of the time of the day Social distancing and worrying about the economic situations have the greatest changes among variables of the study figure (10).

When the mental health status is not very good figure (11) the variables referring to worrying about getting infected with the virus, coping strategies and social distancing have the highest changes in the mental health status for the Egyptians.

Finally, for the worst mental health status being more worried about the economic situation decreases the probability of not feeling good, and increasing monthly total income has a higher effect on decreasing the probability of not feeling good mentally.

1. **Conclusions**

The COVID-19 pandemic has profoundly impacted the labor market, leading to widespread job losses, business closures, and economic instability [63], [34] , [64], [65]. The study shows that when the direction of the change in income increases, people who are more worried about getting infected, younger people, people who aren't mentioned in coping strategies, cases who are committed to social distancing strategies, rural people, those increasing total income, lower education level, and not worried people are more likely to have good mental health status compared to other categories on the survey.

In the study, it was found that when individuals experience good mental health for a significant portion of the day, their income fluctuations and adherence to social distancing guidelines have the most substantial impact among all the factors considered. Conversely, factors such as age and educational level exert minimal influence on altering their mental well-being. For those whose positive mental health occurs less frequently during the day, social distancing practices and concerns about economic conditions exhibit the most significant variations among the variables studied. In situations where mental health is notably poor, variables related to fears of contracting the virus, coping mechanisms, and adherence to social distancing guidelines have the most pronounced effects on mental well-being among Egyptians. Furthermore, in instances of the poorest mental health, heightened concerns about economic conditions decrease the likelihood of feeling mentally well, while an increase in monthly income plays a more significant role in reducing the chances of experiencing poor mental health.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests, OR personal relationships that could have appeared to influence the work reported in this paper.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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