Investigating the differences between factors contributing to COVID-19-related Distress among adults grouped by employment status around the world using the CDC Social-Ecological Model

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Abstract

Background: The global COVID-19 pandemic is a Public Health crisis that highlighted socioeconomic inequities and put an unprecedented strain on the already struggling healthcare and social support systems. In addition to the biologic threat, the pandemic took a toll on mental wellbeing of its intended hosts with multiple sources reporting mental health deterioration in various groups of people.

Objectives: The current study seeks to uncover group differences based on employment status and other variables of interest in terms of demographics and multiple variables contributing to COVID-19 related distress. Grouping variables based on tiers of CDC Social-Ecological Model (SEM) is useful in uncovering significant relationships that would not be found otherwise, and to identify appropriate stakeholders. The ultimate goal for discovering group differences, and hierarchy of independent variables contributing to COVID-19 distress is to develop efficient targeted primary interventions. The broad objective is to create a universal methodology of data analysis that can be utilized to create primary interventions of varying scopes and fields.

Methods: A global de-identified data set based on survey responses gathered at the start of the pandemic was analyzed using SPSS. ANOVA and Chi-square analyses were implemented to discover differences in subgroups based on employment status. Multi-question measures were split up along the CDC SEM levels. Multiple stepwise linear regression was used to model the variables contributing most to COVID-19 distress.

Results: Data confirmed the hypothesis that there are significant group differences in demographics and independent variables contributing to COVID-19 distress. Although significant interactions were discovered by grouping variables by CDC SEM levels that were not significant when considering measure total scores, no particular CDC level was shown to be the top contributor to COVID-19 distress.

Conclusions: The development and implementation of the methods utilized in this project provide a reliable framework for future targeted primary interventions. Similar methods can be adapted utilizing Health Belief Models or other SEMs to promote COVID-19 vaccination efforts. The statistical analysis implemented here can be easily adapted to construct other primary interventions with targeted focus on independent variables most responsible for the greatest variance in desired outcomes.

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At the time of submission, 128M COVID-19 infections and 2.8M COVID-19 deaths have been reported worldwide (Dong et al., 2020). The virus had spread to all continents and 219 countries despite the attempts to contain it, resulting in a global Public Health crisis that highlighted socioeconomic inequities and put an unprecedented strain on the already struggling healthcare systems. In addition to the biologic threat, the pandemic (and the response to it) took a toll on economic stability and mental wellbeing of its intended hosts. A growing body of literature on the psychological effects of the virus has emerged, with multiple studies confirming that mental wellbeing is inversely correlated to various stressors and mediated by resiliency factors (Cullen et al., 2020; Usher et al., 2020; Vindegaard & Benros, 2020). Although the decrease in mental health is evident in the global population, psychiatric symptoms have been reported greater (in both frequency and severity) among health care workers in the US (Vindegaard & Benros, 2020). That is not to imply that non-healthcare essential workers are exempt from the burdens of the pandemic. Even though they are not tasked with aiding the severely ill, they can be low-wage earners who are expected to interact with the public and each other in close proximity and are susceptible to moral injury when their employers fail to provide them with personal protective equipment and a safe work environment (Gaitens et al., 2021). It is no surprise that people who have to work during the pandemic have to face more risk, as in addition to the stress experienced by the unemployed population, they may toil in a hazardous work environment which is often understaffed, and are subject to increasing pressures from management (Huffman et al., 2020; Ke & Hung, 2020; Heath et al., 2020). Conversely, the unemployed may experience more worry due to financial strain to their resources. The variability in the components that are responsible for COVID-19 distress between groups of people must be defined in order to develop targeted interventions that may either be primary (preventing the distress from forming) or secondary (promoting people's ability and self-efficacy to deal with the distress already present).

With so many variables to consider, it would be useful to group them within the constructs of established models used in defining issues pertinent to the pandemic. To define the causes of COVID-19 distress and to identify stakeholders responsible for those causes, a Social-Ecological Model (SEM) framework would work well. Out of the most popular options (eg.: Bronfenbrenner, McLeroy, CDC, Simmons-Morton, McLeroy & Wendel etc.) the CDC model is a prime candidate, not only for its relative simplicity (Richard et al., 2011), but also due to its developmental purpose – to combat violence (as illness is a form of biological violence). The CDC model (Supplemental Figure 1.) subdivides the Social-Ecological environment into 4 levels of influence (Individual (ex. biologic, personal factors), Relationship (ex. family, social circle), Community (ex. school, work, neighborhood), and Society (ex. cultural norms, policy). This approach has been utilized by others to study vaccine acceptance (Kolf et al., 2018; Kumar et. al., 2012), and would be useful to study the present pandemic's adversity.

Fortunately, with reality being a function of subjective perceptions, we can learn a great deal by reframing experiences of adversity as opportunities for growth. The pandemic contributed to technological advancements in telemedicine and remote work, sped up vaccine development, and inspired a boom in clinical research. If one considers the COVID -19 pandemic to be a stress test for humanity, research could be done to explore relationships between various stressors and the effects they have on overall wellbeing. The objectives of this study are to investigate group differences between variables contributing to COVID-19 Distress, develop statistical methods that can be used to target future interventions to groups of interest by focusing on variables with the most impact to those groups, and translate lessons learned to be applicable to future pandemics or environmental disasters potentially contributing to policy and governmental responses. Focusing on the global worker population, this study will also shine light on the contributing factors to COVID-19 distress as related to the workplace, which can be addressed by conscientious leadership while building a more resilient workforce of tomorrow.

Methods

This study relies on the data collected from surveys consisting of several questionnaires from participants across the globe and has been used in a series of papers exploring the effects of COVID-19 on mental wellbeing in the healthcare setting.

Hypotheses

This particular study has 2 main hypotheses:

1. There will be significant differences between the people who experienced a change in employment status, those who were employed prior to and during the pandemic, and those who were consistently unemployed around the globe when it comes to demographic factors and factors contributing to COVID-19 Distress.

2. CDC level 3 factors (e.g.: change in work hours, change in child-care hours, difficulty working from home, positive physical environment, and positive social environment) will be stronger predictors of the outcome variable (Covid-19 Distress) than CDC level 1 factors (e.g.: Medical and Mental Prior Diagnoses).

Exploratory analysis considering alternative grouping variables including prior mental health diagnoses, gender, and belief of risk will also be conducted.

Participants

The participants included adults over 18 years of age with no upper age limit. The upper age limit was not included because there are differences in retirement ages between countries and between genders within countries, because people often work past the age they are qualified to retire, and because the pandemic brought people out of retirement. Participants who reported working more than 150 hours a week were excluded because they likely did not understand the question. The 2937 participants in the data sample were originally subdivided into 4 groups (Table 1). However, due to the low number of participants in the Employed_After group (*n* = 21, 0.7%), we had to separate the employment status variable into 3 groups by combining Employed_After and Employed_Before to form the Employment_Change group (Table 2). The 3 employment groups differed in the number of participants: Employed Both (*n* = 1952), Employment Change (*n* = 427), Unemployed Both (*n* = 558). The vast majority of respondents in all 3 employment groups were females, Hispanic or White, with college or graduate education (Table 3). The Unemployed were older, and had less COVID-19 distress, less COVID-19 worry, and more medical diagnoses (Table 4).

Table 1

Initial employment status grouping variable – Employment_Status4grp

	Before	After	Coded Variable	N	% of Total
Employed_After	0	X	1	21	0.7%
Employed_Before	X	0	2	406	13.8%
Unemployed_Both	0	0	0	558	19%

Employed_Both	X	X	3	1952	66.5%
Total				2937	100%

Table 2

The final employment status grouping variable – Employment_Status3grp

	Before	After	Coded Variable	N	% of Total	N	% of Total
Employment_Change	0 X	X 0	1	21 406	0.7% 13.8%	427	14.5%
Unemployed_Both	0	0	0	558	19%	558	19%
Employed_Both	X	X	2	1952	66.5%	1952	66.5%
Total				2937	100%	2937	100%

Procedure

The original data set was collected under IRB approval of University of Indiana. It had been de-identified and used with permission. Data collection began March 29, 2020 by recruiting adults from the general population via social media advertisements on Reddit, Twitter, Facebook, Instagram, and Qualtrics Panels. The advertisement led to the study page where people signed the informed consent prior to starting the survey.

Constructs and Measures

The survey began with the demographics, which included age, gender, race, education, income, prior medical and mental health diagnoses. This study only used a subset of all data gathered as relevant to the aims and hypotheses. Single item variables such as work hours, childcare hours, difficulty working from home, positive physical and social environment, medical conditions, and mental health conditions were pulled from larger measurement instruments. COVID-19 risk was also a single item yes/no question asking if the participant believed they were at risk. The following are the multiple-item measures that were used in this study:

COVID-19 Coping – Corona virus and social distancing Questionnaire is an 11-item instrument judged on a 5-point Likert scale (*strongly disagree* to *strongly agree*). It was further subdivided into 3 parts based on the CDC SEM: CDC1 Coping, CDC2 Coping, and CDC3 Coping.

COVID-19 Distress is a 12-item instrument judged on a 5-point Likert scale (*not at all* to *extremely*) that addresses CDC distress symptomology (eg.: anger/fear, novel bother, sadness, adversity, substance abuse). The higher the total score, the greater the distress.

COVID-19 Worry is a 12-item instrument judged on a 4-point Likert scale (*not worried* to *very worried*). It is composed of questions about being infected, becoming seriously ill, being unable to access necessities, becoming unemployed and less financially stable that participants first answer about themselves, and then their loved ones. It was further subdivided into 2 levels based on CDC SEM: 6 questions of personal worry (CDC1) and 6 questions of family worry (CDC2). The personal worry and worry for others produced a combined score of total worry.

COVID-19 History is a 6-item instrument asking yes/no questions about COVID-19 symptoms (symptoms now, previously, ever) and COVID-19 diagnoses (diagnosis now, previously, ever).

Help-Seeking is a 9-item instrument asking people about their help-seeking behavior. It is subdivided into 2 CDC SEM categories: CDC2 (e.g.: help from partner, friend, parent, or other relative) and CDC 3 (eg.: help from medical and mental health professionals, help lines, and religious leaders).

The statistical analysis was conducted via SPSS. Cronbach's alpha was calculated for multi-question instruments to determine internal consistency within the study sample.

COVID-19 Worry: n=2920 standardized alpha=.858

COVID-19 History: n=2932 standardized alpha=.710

COVID-19 Distress: n=2899 standardized alpha=.920

Help Seeking Behavior: n=2824 standardized alpha=.666

COVID-19 Coping (Coronavirus and Social Distancing Questionnaire): n=2696 standardized alpha=.478

One-way ANOVA and Chi-Square was used to determine group differences within variables. Stepwise multiple linear regression was used to determine the coefficients of the final models and to identify variables contributing most to variability of COVID-19 Distress within groups. Additional variables that had to be created from the original dataset in SPSS to complete the above measures are listed below:

COVID_WorryOthers = [COVID_WTotalorry] - [covid_3_indexWorrySel]

COVIDHistoryEver = [COVIDSymptomsEver]+[COVIDDiagnosisEver]

Childcarehourschange = [covid_13Childcarehoursafter] – [covid_12Childcarehoursbefore]

Covid_14_TotalCoping = sum(covid_14_1FeelCrowded+… covid_14_11SleepLess)

- ***CDC1_covid_14*** = [covid_14_7CareForBody] + [covid_14_8StayCOVIDInformed] + [covid_14_9KeepBusy] + [covid_14_10AvoidThinkingCOVID] + [covid_14_11SleepLess]
- ***CDC2_covid_14*** = [covid_14_5FeelSociallyConnected] + [covid_14_6SupportFromPets]
- ***CDC3_covid_14*** = [covid_14_1FeelCrowded] + [covid_14_2SafeOutdoors] + [covid_14_3ComfortableClimate] + [covid_14_4SeeSunshine]

HelpFromPeopleTotalScore = sum(CDC2_Help + CDC3_Help)

- ***CDC2_Help*** = [HelpFromIntimatePartner] + [HelpFromFriendnotrelated] + [HelpFromParent] + [HelpFromOtherRelattive]
- ***CDC3_Help*** = [HelpFromMHProfession] + [HelpFromPhoneHelpLine] + [HelpFromMedicalProfesional] + [HelpFromReligiousLeader]

Results

The data shows that employment groups differed based on the following demographic factors: gender, race (significant only for White and Asian races), education level, COVID diagnosis, other medical diagnoses, and belief of being at risk for COVID (Table 3).

Table 3

Demographic Characteristics by Groups (ANOVA and Chi-Square)

	Employment Change	Employed Both	Unemployed Both	*F or X^2*	*p*
Gender				*X^2 = 26.848*	*.000*
Female	75.0%	73.3%	65.4%	*X^2 = 15.869*	*.000*
Male	23.1%	25.5%	34.5%	*X^2 = 21.221*	*.000*

Other	1.9%	1.1%	0.2%		
Racial Groups					
Asian	8.8%	4.5%	4.9%	*F = 8.480*	*.014*
Black or African American	8.8%	8.7%	7.9%	*F = .279*	*.870*
Hispanic	81.3%	86.2%	86.0%	*F = 4.425*	*.109*
White	67.4%	73.4%	76.2%	*F = 6.711*	*.035*
Highest Education Level				X^2 *= 271.271*	*.000*
Primary/Vocational School	3.5%	1.4%	1.6%		
Secondary School	12.2%	7.0%	24.2%		
College	49.2%	29.8%	41.6%		
Graduate School	35.1%	61.8%	32.6%		
COVID Diagnosis Now	1.2%	2.2%	0.4%	X^2 *= 9.687*	*.008*
COVID Diagnosis Ever	3.8%	4.5%	0.9%	X^2 *= 15.590*	*.000*
COVID Diagnosis Previously	2.6%	2.3%	0.5%	X^2 *= 7.564*	*.023*
Any MH Diagnosis	41.5%	44.1%	44.6%	X^2 *= 1.185*	*.553*
Therapy Currently	23.7%	24.4%	24.4%	X^2 *= .106*	*.949*
Therapy Never	31.9%	26.6%	38.4%	X^2 *= 29.742*	*.000*
Any Med Diagnosis	19.9%	21.6%	29.4%	X^2 *= 17.479*	*.000*

Believed at Risk	10.1%	8.9%	12.5%	*$X^2 = 6.756$*	*.034*

There were significant group differences in the variables contributing to COVID-19 distress among the different employment groups considered (Table 4). Differences in age, education, income, COVID-19 distress, COVID worry (except worry of being infected and being unable to get medication), belief of being at risk, change in work hours, difficulty working from home, positive physical and social environments, help seeking, and COVID coping (except for CDC3 level coping) were all statistically significant among employment groups considered. Curiously, none of the childcare hours variables were significantly different among employment groups. That may be because childcare hours almost doubled for everyone with children regardless of employment status because of school and daycare closures during the pandemic. It could also be due to the fact that people overburdened with childcare are likely not spending time on social media where they would see the advertisement to participate in the study, or if they do see it, they may not have the time to fill out the survey.

Table 4

ANOVA group differences for variables contributing to COVID – 19 Distress

	Employment Change	**Employed Both**	**Unemployed Both**		
	M (SD)	**M (SD)**	**M (SD)**	***F*=**	***p*=**
Age	45.00(15.45)	45.51(13.39)	54.04(17.18)	*77.26*	*.000*
Education4grp	3.16(0.77)	3.52(0.69)	3.05(0.79)	*114.50*	*.000*
Income Linear	3.18(1.82)	4.30(1.79)	2.96(1.85)	*107.99*	*.000*

COVID Distress Total	27.17(11.27)	25.82(10.12)	24.04(10.47)	*11.52*	*.000*
COVID Worry	15.88(9.15)	14.06(8.43)	12.69 (8.55)	*16.66*	*.000*
Personal Worry	7.87(4.73)	6.60(4.43)	6.00(4.19)	*22.30*	*.000*
Be Infected	1.29(0.96)	1.33(0.92)	1.39(0.97)	*1.40*	*.248*
Seriously Ill	1.23(1.03)	1.25(0.96)	1.39(1.05)	*5.23*	*.005*
Lack Necessities	1.04(1.07)	0.86(0.98)	0.98(1.04)	*6.78*	*.001*
Less Financially Stable	1.92(1.14)	1.42(1.07)	1.10(1.09)	*69.40*	*.000*
Unable to get Medication	0.87(1.00)	0.79(0.98)	0.84(1.01)	*1.70*	*.183*
Lose job	1.53(1.27)	0.95(1.06)	0.31(0.81)	*163.21*	*.000*
Worry Others	8.00(5.05)	7.47(4.59)	6.70(4.93)	*9.73*	*.000*
COVID Believe at Risk	0.10(0.30)	0.09(0.28)	0.13(0.33)	*3.38*	*.034*
COVID-19 History					
COVID-19 Symptoms Now	0.05(0.22)	0.05(0.22)	0.03(0.17)	*1.75*	*.173*
COVID-19 Symptoms Ever	0.23(0.42)	0.22(0.42)	0.13(0.33)	*13.32*	*.000*
COVID-19 Diagnosis Previously	0.03(0.16)	0.02(0.15)	0.01(0.07)	*3.79*	*.023*

Prior Diagnoses					
Any Medical	0.20(0.40)	0.22(0.41)	0.29(0.46)	*8.78*	*.000*
Total Mental	0.73(1.04)	0.72(1.04)	0.78(1.06)	*0.86*	*.424*
Therapy Currently	0.24(0.43)	0.24(0.43)	0.24(0.43)	*0.05*	*.949*
Therapy Never	0.32(0.47)	0.27(0.44)	0.38(0.49)	*15.01*	*.000*
Change in Work Hours	-25.74(17.57)	-4.90 (13.07)	0(0)	*586.77*	*.000*
Difficulty Working from Home	3.17(1.54)	3.37(1.41)	3.78(1.31)	*14.34*	*.000*
Change in Child Care Hours	30.30(37.60)	23.93(55.00)	47.56(316.93)	*1.65*	*.193*
Childcare Hours Before	49.71(60.27)	52.00(86.20)	45.74(51.67)	*0.33*	*.718*
Childcare Hours After	80.02(72.64)	75.88(111.91)	93.30(320.09)	*0.62*	*.539*
Positive Physical Environment	14.76(2.77)	15.03(2.77)	15.29(2.76)	*4.53*	*.011*
Positive Social Environment	6.42(1.96)	6.98(1.83)	6.25(2.10)	*36.50*	*.000*
Help Seeking Total	23.87(9.05)	26.15(8.51)	23.81(8.61)	*22.64*	*.000*
CDC2 Help	17.24 (SD)	15.89 (SD)	16.28 (SD)	*56.87*	*.000*
CDC3 Help	6.63 (2.61)	10.26 (2.44)	7.53 (2.45)	*8.46*	*.000*

COVID-19 Coping Total	37.97(4.73)	38.93(4.81)	37.84(4.81)	*13.94*	*.000*
CDC1 Coping	17.18(2.62)	17.61(2.43)	17.23(2.46)	*8.48*	*.000*
CDC2 Coping	6.42(1.96)	6.98(1.83)	6.25(2.10)	*36.50*	*.000*
CDC3 Coping	14.32(2.63)	14.33(2.54)	14.34(2.48)	*0.01*	*.994*

Data also shows that the variance in COVID-19 distress is accounted for by different independent variables within all the groups considered (Table 5 and Table 6). The first hypothesis, that there will be significant differences between the people who experienced a change in employment status, those who were employed prior to and during the pandemic, and those who were consistently unemployed around the globe when it comes to demographic factors and factors contributing to COVID-19 Distress is supported by the data.

Table 5

Final Models of Multiple Stepwise Linear Regression predicting COVID-19 Distress

Predictor Variables	SB Coeff	*p*	Predictor Variables	SB Coeff	*p*	Predictor Variables	SB Coeff	*p*
Employment Change $R^2 = .579$ $F(6, 39) =$ 11.31		*.000*	**Employed Both** $R^2 = .378$ $F(5, 314) =$ 39.82		*.000*	**Unemployed Both** $R^2 = .575$ $F(4, 49) =$ 18.90		*.000*
Total MH Diagnoses	.348	*.002*	Worry Self	.436	*.000*	Total Worry	.562	*.000*
CDC3 COVID Coping	.639	*.000*	Any MH Diagnoses	.270	*.000*	Age	-.239	*.018*

Positive Physical Environment	-.471	*.000*	Positive Physical Environment	-.230	*.000*	Total MH Diagnoses	.260	*.009*
Any Med. Condition	-.353	*.001*	Income linear	.157	*.001*	Childcare hours before	.246	*.011*
Age	.272	*.015*	CDC3 COVID Coping	.144	*.007*			
Childcare hours after	.265	*.016*						

			All Groups					
			$R^2 = .391$					
			$F(7, 412) =$ 39.44		*.000*			
			Worry Self	.450	*.000*			
			Total MH Diagnoses	.276	*.000*			
			Difficulty WfH	-.079	*.047*			
			Income linear	.140	*.001*			
			Age	-.098	*.018*			
			Positive Physical Environment	-.184	*.000*			
			CDC3 COVID Coping	.164	*.000*			

Note. In Stepwise Linear Regression, R^2 is the percent of variability accounted for by the predictors.

Table 6

Final Models of Multiple Stepwise Linear Regression predicting COVID-19 Distress in exploratory groups

Predictor Variables	Coefficient	*p*	Predictor Variables	Coefficient	*p*
No MH Diagnoses			**Any MH Diagnosis**		

$R^2 = .219$			$R^2 = .408$		
F(4, 180) = 13.90, *p* = .000			*F*(6, 228) = 27.84, *p* = .000		
Worry Self	.321	.000	Worry Self	.571	.000
Childcare Hours Before	.180	.007	Total MH Diagnoses	.138	.008
Positive Physical Environment	-.189	.008	Income Linear	.144	.007
Education 4grp	.161	.016	CDC2 Help	-.130	.015
			CDC3 COVID Coping	.226	.000
			Positive Physical Environment	-.220	.001
Female			**Male**		
$R^2 = .321$			$R^2 = .519$		
F(6, 266) = 22.48, *p* = .000			*F*(4, 142) = 40.32, *p* = .000		
Worry Self	.408	.000	Worry Self	.503	.000
Total MH Diagnosis	.305	.000	Any MH Diagnoses	.275	.000
Difficulty WfH	-.169	.001	Positive physical Environment	-.265	.000
Positive Social Environment	-.153	.004	CDC3 COVID Coping	.206	.004
CDC1 COVID Coping	.137	.010			
Income Linear	.120	.024			
Believed at Risk			**Not Believed at Risk**		
$R^2 = .298$			$R^2 = .401$		
F(2, 24) = 6.52, *p* = .005			*F*(8, 384) = 33.75, *p* = .000		
Age	-.423	.017	Worry Self	.455	.000
Total MH Diagnoses	.410	.020	Total MH Diagnoses	.176	.007
			Difficulty WfH	-.082	.045

			Income Linear	.110	.007
			Childcare Hours After	.105	.009
			Positive Physical Environment	-.181	.000
			CDC3 Coping	.145	.003
			Any MH Diagnoses	.139	.032

Note. In Stepwise Linear Regression, R^2 is the percent of variability accounted for by the predictors.

Multiple Stepwise Linear Regression models:

The equations to the regression models that emerged from this data analysis are listed below.

<u>General Model:</u>

Change in COVID-19 Distress = 19.902+.450(Worry Self)+.276(Total MH Diagnoses)-.079(Difficulty WfH)+.140(Income Linear)-.098(Age)-.184(Positive Physical Environment)+.164(CDC3 COVID Coping)

<u>Employment Change Group Model:</u>

Change in COVID-19 Distress = 10.920+.348(Total MH Diagnoses)+.639(CDC3 COVID Coping)-.471(Positive Physical Environment)-.353(Any Medical Condition)+.272(Age)+.265(Childcare Hours After)

<u>Employed Both Group Model:</u>

Change in COVID-19 Distress = 16.675+.436(Worry Self)+.270(Any MH Diagnoses)-.230(Positive Physical Environment)+.157(Income Linear)+.144(CDC3 COVID Coping)

<u>Unemployed Both Group Model:</u>

Change in COVID-19 Distress = 18.355+.562(Total Worry)-.239(Age)+.260(Total MH Diagnoses)+.246(Childcare Hours Before)

<u>No MH Diagnosis Group Model:</u>

Change in COVID-19 Distress = 19.032+.321(Worry Self)+.180(Childcare Hours Before) -.189(Positive Physical Environment)+.161(Education 4grp)

<u>Any MH Diagnosis Group Model:</u>

Change in COVID-19 Distress = 16.083+.571(Worry Self)+.138(Total MH Diagnoses)+.144(Income Linear)-.130(CDC2 Help)+.226(CDC3 COVID Coping)-.202(Positive Physical Environment)

<u>Females Group Model:</u>

Change in COVID-19 Distress = 13.694+.408(Worry Self)+.305(Total MH Diagnoses)-.169(Difficulty WfH)-.531(Positive Social Environment)+.137(CDC1 COVID Coping)+.120(Income Linear)

<u>Males Group Model:</u>

Change in COVID-19 Distress = 18.520+.503(Worry Self)+.275(Any MH Diagnoses)-.265(Positive Physical Environment)+.206(CDC3 COVID Coping)

<u>Believed at Risk Group Model:</u>

Change in COVID-19 Distress = 36.701-0.423(Age)+.410(Total MH Diagnoses)

<u>Not Believed at Risk Group Model:</u>

Change in COVID-19 Distress = 15.762+0.455(Worry Self)+0.176(Total MH Diagnoses)-0.082 (Difficulty WfH)+0.110(Income Linear)+0.105(Childcare Hours After)-0.181(Positive Physical Environment)+0.145(CDC3 COVID Coping)+0.139(Any MH Diagnoses)

Worry for Self was #1 predictor of COVID-19 distress among several groups: All participants, Employed Both, no MH diagnosis, any MH diagnoses, females, males, and those who did not believe they are at risk for COVID. The finding that even the people who did not believe they are at risk for COVID are still experiencing COVID distress primarily as a result of worrying for themselves is curious. It may be due to the fact that younger people who are not immunocompromised and therefore not under any additional medical risk, are the ones who have to work during the pandemic and expose themselves to occupational hazards because they are less financially stable than older people. CDC3 COVID Coping variable was a significant model predictor for All groups, Employment Change, Employed Both, Any MH Diagnosis, males, and those who did not believe they were at risk, while Total COVID Coping was not significant for any groups. CDC1 COVID Coping variable was a significant predictor for females, while Total Coping was not. CDC2 Help variable was a significant predictor for people with any MH Diagnosis while Total Help was not. These findings show that grouping variables by CDC social-ecological levels does uncover interactions that would have been missed if only the total instrument variables were used but does not support CDC3 level variables being most influential contributors to COVID-19 distress. The second hypothesis, that CDC level 3 factors (e.g.: change in work hours, change in child-care hours, difficulty working from home, positive physical environment, and positive social environment) will be stronger predictors of the outcome variable (Covid-19 Distress) than CDC level 1 factors (e.g.: Medical and Mental Prior Diagnoses) is therefore not supported by data.

Discussion

Overall, this study exhibited a promising statistical approach to development of targeted interventions. Group differences based on employment status as well as other variables of interest can be effectively identified using ANOVA and Chi-Square. Multiple stepwise linear regression models are an appropriate tool of choice when it comes to ranking independent variables in order of magnitude of effect on the variance in the dependent variable. This approach is instrumental in focusing resources and time into addressing variables that have the most potential to affect the dependent variable, and if used in the design of interventions, would contribute to the efficiency of said interventions.

Strengths and Limitations

A prominent strength of this study is the large sample size (*n* = 2937) and the fact that the survey was available to the global population. However, the sample is not a representative sample of the global population, which is a limitation and a detriment to generalizability. There is not a proportional number of respondents from each country that had responses, and the majority of participants came from English-speaking regions of North America, which is also a generalizability detriment. Subjects had to have access to technology and internet to participate, which favors those of higher socio-economic status and those residing in most developed regions of the globe. The study sample was also subject to self-selection bias, meaning that fundamental traits of people who would participate in the study may be mediating or confounding variables in the cause-effect path to the dependent variable of the study. Despite these limitations, this study captured data in the beginning of the pandemic, which was reflective of fresh changes with minimal pandemic burnout in responses. The data and statistical approach implemented effectively shows that subdividing variables based on CDC levels allows measures that do not significantly affect COVID-19 Distress when considered cumulatively to have significant effect within certain socio-ecological levels. The tactic of nesting established models into large data sets permits researchers to see the bigger picture of the patterns and interactions of the variables of interest. However, a major limitation of the CDC model chosen is that there were no variables representing CDC level 4 in the data set, so the model is incomplete *a priori*. A post hoc analysis to add CDC level 4 variables like GDP of participant's country, regional religions, governmental structure and policy, and more were considered. Ultimately, due to rapid policy developments in the beginning of the pandemic, and the uncertainty of the validity of data as it is subject to governmental information suppression, no CDC level 4 variables were created. Had it been practical to create such variables, there were no questions in the data set to gauge the respondents' perceived influence from variables of that hierarchy. Last, but not least, variable interactions do exist between CDC SEM levels, therefore they cannot be strictly separated. The classification of questions into those levels is subjective and open to interpretation.

Implications

This study showed that different groups of people have different hierarchy of predictor variables for COVID-19 Distress. Different adjusted R^2 for final regression models show differences in % of variability in COVID-19 Distress that can be accounted for by predictor variables. Therefore, this data analysis approach can be useful in targeted intervention development that both focuses on particular populations of interest and the most influential variables within those populations. Such precision is important for interventions that lack ample funding, which many Public Health interventions do.

Future recommendations

By the time of paper submission, the world is in the middle of vaccination efforts and re-opening of economies. One of the recommendations emerging from this work is to use a similar statistical analysis approach to facilitate COVID-19 vaccine adoption and distribution. The use of SEMs to facilitate vaccine adoption has been explored in the past (Kolff et al., 2018; Kumar et al., 2012). Other studies have also began grouping data based on the variables in the Health Belief Model in order to predict, monitor, and encourage vaccine adoption (Brewer et al., 2007; Wong et al., 2020), with some already applying the findings to the COVID-19 pandemic (Wong et al., 2020).

Another future recommendation stemming from this work is to use a similar statistical approach to monitor factors contributing to general non-pandemic related distress in academic, educational, and organizational environments with the goal of developing level 1 evidence-based interventions to address the root causes instead of relying solely on level 2 mindfulness and resilience interventions that place the onus on those experiencing the distress to cope better with it. Future work is needed to persuade organizational leaders and stakeholders that taking responsibility for distress causes and addressing them is beneficial to both organizations and workers that keep them running. That is not to say that mindfulness-based interventions are ineffective, just that they can not be solely relied on to promote wellbeing when the option to address the stressors directly is also available.

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Supplemental Figure 1

CDC Social-Ecological Model