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Burnout, depression and hours of sleep among nursing and medical professionals in Peru: a network analysis

Burnout, depresión y horas de sueño en personal de enfermería y medicina de Perú: un análisis de redes

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Abstract

Healthcare professionals are one of the most vulnerable groups to suffer burnout due to situations of high work pressure, work schedules and rotating schedules, which can increase the probability of developing depression and sleep problems. However, to date, no analysis has been implemented to evaluate the interaction between burnout, depression and sleep hours in physicians and nurses in Peru. Therefore, the aim of the study was to examine the correlation between the components of burnout, depression and hours of sleep in Peruvian nursing and medical professionals. Information was obtained from 2216 physicians (M_{age} = 45.55, SD = 11.50) and 2882 nurses (M_{age} = 44.63, SD = 11.09) chosen with probability sampling, who were administered the Maslach Burnout Inventory- Human Service Survey and the Patient Health Questionnaire-2. Network analysis was performed in R software and network invariance was calculated at the global level and at global strength level. The results indicated that, emotional exhaustion was the central node, which correlates with depression and hours of sleep. It was concluded that the hours of sleep are associated to a greater extent with emotional exhaustion, in addition, the network was invariant according to profession.

Keywords: Burnout; depression, sleeping hours, nursing, medicine.

Resumen

El personal sanitario es uno de los grupos más vulnerables a sufrir burnout debido a situaciones de alta presión laboral, horarios de trabajo y horarios rotativos Esto puede aumentar la probabilidad de sufrir depresión y problemas de sueño. Sin embargo, hasta la fecha no se ha implementado un análisis que evalúe la interacción entre burnout, depresión y horas de sueño en médicos y enfermeras en el Perú. Por lo tanto, el objetivo del estudio fue examinar la correlación entre los componentes de burnout, la depresión y las horas de sueño en profesionales de enfermería y medicina de Perú. Se obtuvo información de 2216 médicos (M_{edad} = 45.55, DT = 11.50) y 2882 enfermeras (M_{edad} = 44.63, DT = 11.09) elegidos con muestreo probabilístico, a quienes se les administró el Maslach Burnout Inventory- Human Service Survey y el Patient Health Questionnaire-2. Se realizó un análisis de redes en el software R y se calculó la invarianza de red a nivel global y a nivel de la fuerza de las aristas. Los resultados indicaron que, el agotamiento emocional fue el nodo central, el cual correlaciona con la depresión y las horas de sueño. Se concluyó que las horas de sueño se asocian en mayor medida con el agotamiento emocional, además, la red fue invariante según profesión.

Palabras clave: Burnout; depresión, horas de sueño, enfermería, medicina.

INTRODUCTION

Burnout (BO) is defined as a response to chronic interpersonal stressors that are present in a work context and is characterized by emotional exhaustion, negative attitudes or responses towards others and feelings of lack of personal fulfillment (Maslach *et al.*, 2001, 2008). In the same vein, the World Health Organization (WHO, 2019) considers it a syndrome produced by constant stress given in a work context whose characteristics are a feeling of tiredness, distancing from work and a reduction in work performance. However, it is not a medical condition but an occupational phenomenon, which is classified in ICD-11 and denotes the importance of BO over different aspects in workers' lives. Even, the International Labor Organization (ILO, 2016, 2022) has pointed out that BO has an impact on mental health, as BO can lead to depression, anxiety, suicide and premature death. Also, on productivity, which leads to economic costs for employers and employees.

Although this syndrome can affect any profession, health personnel, such as nurses or physicians, are those who usually present higher levels of BO (Carrillo-Esper *et al.*, 2012) because they are exposed to situations of high pressure, long working hours, rotating schedules and even aggressions by patients or their families (García-Iglesias *et al.*, 2021; López-López *et al.*, 2019). In fact, figures indicate that between 48.88 % and 67 % of physicians present high levels of BO (Cobo *et al.*, 2019; Rotenstein *et al.*, 2018; Trujillo *et al.*, 2020). Likewise, it has been reported that about 30 % of the nursing staff present BO (Adriaenssens *et al.*, 2015; Monsalve-Reyes *et al.*, 2018; Pradas-Hernández *et al.*, 2018; Rezaei *et al.*, 2018).

This reality is not foreign to Latin America, as it has been found that BO is present in healthcare personnel throughout the different countries of the region. Thus, a review study that included a medical population found that the prevalence of BO in Argentina is between 15.9 % and 80.2 %; in Brazil it was between 2.4 and 83.3 %; Costa Rica presented 72 % of incidence; Chile 64.4 %; Colombia 28 %; Ecuador between 2.6 and 12 %; Uruguay 51 %, Venezuela between 56.7 % and 64.1 %. Finally, in Peru the prevalence was between 2.8 and 28 % (Vásquez-Navas & Gea-Izquierdo, 2023). However, the most recent data from a systematic review developed with health personnel reported an incidence of 27 %, 48 % and 17 % in low, medium and high BO levels, respectively (Yslado *et al.*, 2024b).

Given the above, the study of BO becomes relevant, even more so when studies indicate its link with depression, anxiety, sleep problems, irritability, substance use, work overload (Fischer *et al.*, 2020; Pradas-Hernández *et al.*, 2018), suicide, increased likelihood of making medical errors, job dissatisfaction, among other negative consequences in the lives of health professionals and their patients (Aryankhesal *et al.*, 2019; Chen & Meier, 2021; Edward *et al.*, 2014; Melnyk, 2020). In this sense, it is important to examine the interaction among the variables involved with BO, such as hours of sleep and depression in this population so that interventions can be designed to reduce this phenomenon and thus improve the mental health of physicians and nurses.

The aforementioned is explained when taking into account that healthcare professionals, working rotating and extended hours due to night calls, patient demands and work overload, their circadian rhythm varies causing fewer hours of sleep and greater exhaustion along with energy drain (Stewart & Arora, 2019), which, in addition, predicts depression (Weaver *et al.*, 2020); this is coupled with high caffeine consumption that mitigates sleepiness (Clark & Landolt, 2017; Stewart & Arora, 2019). Likewise, it has been reported that the workload also prevents socializing with family and having leisure time due to sleep problems, which are protective factors against depression. Therefore, such absence could increase the likelihood of occurrence of depressive symptomatology and even suicidal ideation (Steiger & Pawlowski, 2019; Stewart & Arora, 2019). Indeed, among the core symptoms of depression are fatigue and sleep disorders (e.g., insomnia; Nutt *et al.*, 2008).

One of the techniques that allow examining the relationships and interaction of clinical variables is network analysis (Isvoranu *et al.*, 2021), which also allows knowing which is the most important symptom so that interventions can be focused on it by means of centrality indexes (Fonseca-Pedrero, 2017). However, studies that have implemented this technique to investigate BO are still scarce. In fact, antecedents using network analysis have found that emotional exhaustion ("EE") - the main component of BO - was more strongly related to depression than depersonalization (DES) and personal fulfillment (PF; Verkuilen *et al.*, 2021). A second study reported that EE is mainly related to depression and stress, with this triad being the most central (Nezkusilova *et al.*, 2020). A third investigation found that item 8 of the Maslach Burnout Inventory (I feel exhausted by my work) was the most relevant indicator of the network associated with anxiety and depression (Fischer *et al.*, 2020). It has also been found that BO was strongly related to compassion fatigue, moderately related to satisfaction and slightly related to insomnia, but not to depression (Tokac & Razon, 2021). Finally, a fourth and more recent study indicated that being exhausted by work and excessive work stress were central indicators of BO in nurses, whereas in physicians the centrality fell on contribution to the hospital (Zhang *et al.*, 2024). However, to date, network analysis has not been implemented to evaluate the interaction between BO, its components (EE, PF and DE), depression and hours of sleep-in physicians and nurses in Peru, nor at the Latin American level, despite the high incidence of these phenomena in this context.

In view of the above, the main objective of the present study was to examine the correlation between the components of BO (EE, PF and DES), depression and hours of sleep in nursing and medical professionals in Peru by means of network analysis. In this sense, the study has a mainly exploratory character that responds to a theoretical gap and fills a gap in knowledge in the national context, since there is a lack of studies that have addressed the interrelation of these phenomena. In addition, the findings could be useful for their practical and social implications, since knowing the links among them contributes to the visibility of this phenomenon among health personnel so that the authorities can promote a culture of care and support in the work context of health workers. This would not only benefit doctors and nurses at the individual level, but also increase the quality of service and patient care. Therefore, the findings can serve as a foundation for developing policies and intervention programs aimed at mitigating BO, promoting healthy sleep habits and thus reducing the likelihood of depression.

METHOD

Design:

The research design is associative and cross-sectional (Ato *et al.*, 2013), since the aim is to know the relationship among variables, but at a given point in time.

Participants:

The total population of health professionals was 60 120 (26 756 physicians and 33 364 nurses). The calculated sample was 5067 (2211 physicians and 2856 nurses), but the final database consists of 5098 professionals in medicine (n = 2216, Median = 45.55, SD = 11.50) and nursing (n = 2882, Median = 44.63, SD = 11.09), who worked in all regions of Peru. Characteristics regarding sex, work shift and marital status are shown in Table 1. Data were obtained from the National Health User Satisfaction Survey (ENSUSALUD, from the Spanish initials) during 2016.

ENSUSALUD is a survey aimed at evaluating the performance of the Peruvian health system and collects information on both external (e.g., patients) and internal users (e.g., physicians, nurses, etc.).

The way in which the ENSUSALUD was developed among health personnel was by means of face-to-face interviews and the sample was selected in a probabilistic, stratified and two-stage way. This implies that in the first phase, health facilities were selected and in the second phase, physicians and nurses were selected; both choices were randomly made and divided into strata (Instituto Nacional de Estadística e Informática [INEI], 2016). In this sense, the sample obtained is representative in the country.

Regarding ethical considerations, the study used a public and freely accessible database that does not contain sensitive information and is therefore anonymous. Therefore, it did not require the approval of an ethics committee. In this sense, it complies with the guidelines set forth in the Declaration of Helsinki for research in humans. The link to the direct download of the file is in .sav format and can be downloaded at the following URL: http://portal.susalud.gob.pe/wp-content/uploads/archivo/base-de- datos/2016/C2_CAPITULOS%20-%20PROFESIONALES%20MEDICOS%20Y%20ENFERMERAS.sav

Table 1

Sociodemographic data of physicians and nurses

		Total		Medicine		Nursing	
		n	%	n	%	n	%
Marital status	Cohabitant	554	10.87	198	8.94	356	12.35
	Married	2829	55.49	1351	60.97	1478	51.28
	Widowed	70	1.37	21	0.95	49	1.70
	Divorced	154	3.02	72	3.25	82	2.85
	Separated	119	2.33	36	1.62	83	2.88
	Single	1372	26.91	538	24.28	834	28.94
Sex	Man	1915	37.56	1673	75.50	242	8.40
	Woman	3183	62.44	543	24.50	2640	91.60
Region	Coast	1516	29.74	670	30.23	846	29.35
	Jungle	1757	34.46	749	33.80	1008	34.98
	Highlands	676	13.26	270	12.18	406	14.09
	Metropolitan Lima	1149	22.54	527	23.78	622	21.58
Institution	MINSA	2401	47.10	1015	45.80	1386	48.09
	ESSALUD	2280	44.72	1029	46.44	1251	43.41
	FF.AA. y PNP	95	1.86	33	1.49	62	2.15
	Clinics	322	6.32	139	6.27	183	6.35
Shift	Morning	3068	60.18	1341	60.51	1727	59.92
	Afternoon	1920	37.66	825	37.23	1095	37.99
	Evening	110	2.16	50	2.26	60	2.08

Instrument

Maslach Burnout Inventory – Human Service Survey (MBI - HSS; Maslach et al., 2001)

The MBI-HSS is a self-report instrument composed of 22 items whose purpose is to evaluate the BO in three dimensions: EE, DES, PF. The response options are on a Likert scale with seven points ranging from Never = 0 to every day = 6. Although the ENSUSALUD does not specify the version used, a reanalysis of the items in the same database indicated that in Peru, for nurses both the 22-item version (CFI =. 974; RMSEA .052; SRMR = .059; ΩAE = .872; ΩDE = .838; ΩRP = .725) and the 15-item version with items 1, 6, 16, 20, 12, 19 and 21 removed (CFI = .972; RMSEA =. 049; SRMR = .047; ΩAE = .797; ΩDE = .837; ΩRP = .810), grouped into three factors, had adequate psychometric properties (Calderón-de la Cruz et al., 2020a). In physicians, the three-dimensional structure has been replicated, but eliminating items 1, 16 and 21 (Calderón-de la Cruz et al., 2020b; CFI = .977; RMSEA = .058; SRMR = .063; ΩAE = .918; ΩDE = .845; ΩRP = .909). More recent studies with health care personnel have found three dimensions with item 15 removed with adequate goodness-of-fit and reliability indices with the exception of depersonalization (Yslado et al., 2024a; CFI = .937; TLI = .929; WRMR = 1.152; SRMR = .075; ΩAE = .883; ΩDE = .492; ΩRP = .802).

Given the lack of consensus on its internal structure, this study chose to consider the 15-item version (Calderón-de la Cruz et al., 2020a) for the following reasons: a) the model is one of those that has obtained the highest fit indices among previous studies; b) the 15 items are shared by the nursing and medical populations, so using a "standardized" version allows comparison among groups; furthermore, c) these decisions are based on psychometric studies that have been developed with nationally representative samples, which has the advantage that the results have a greater degree of generalization.

Patient Health Questionnaire – 2 (PHQ-2; Kroenke et al., 2003)

The PHQ-2 is a self-report instrument with two items, which are the most relevant for assessing depression (PHQ1 = loss of interest and PHQ2 = depressed mood). It has four response options ranging from Never = 0 to Almost every day = 3. The higher the score, the more depression. The original version indicates that a cut-off point > 3 has adequate sensitivity and specificity in detecting depression (Kroenke et al., 2003); furthermore, validity and reliability were demonstrated by criterion validity.

Hours of sleep

The hours of sleep were measured by the question: *On average, how many hours a day do you sleep?* whose code in the ENSUSALUD-2016 is C2P52.

Data analysis

A network analysis was performed in the R statistical software with the Bootnet, qgraph, igraph and Network Comparison Test libraries. Unregularized partial correlations were used to estimate the network by means of the ggmModSelect function, which uses an algorithm that allows finding a network structure in a more balanced way than others. That is, it searches for the most suitable model by iteratively exploring different network configurations, adding or eliminating interconnections between nodes taking into account the one with the best fit and without excessive complexity. To do so, the algorithm considers the most parsimonious structure with the lowest EBIC (Epskamp & Fried, 2018). Spearman correlation matrices were used to estimate the connections, because the variables followed a non-normal distribution (Isvoranu & Epskamp, 2021). It should be noted that to determine normality it was taken into account that if the absolute values of kurtosis and asymmetry exceeded ± 1.5, the distribution of the variables was different from normal (Tabachnick, & Fidell, 2013).

Node centrality was analyzed using the Expected Influence index as it is more appropriate when the network has direct and inverse correlations (Robinaugh *et al.*, 2016). The stability and accuracy of the network were then estimated using a non-parametric Bootstrap - given the lack of normality - with 1000 resamples under the same configuration as mentioned above. This procedure consists of taking successive random samples from the real data and recalculating the network 1000 times with the objective of observing the variation in the structure of the network at the level of edges and centrality. Thus, if there is similarity in each resampling, there would be evidence of a stable and accurate network (Epskamp, 2020). For this purpose, a cutoff point of > .50 for the stability coefficient was taken into account (Epskamp *et al.*, 2018).

Finally, to determine the invariance of the networks and the global invariance of the connection strength of the edges according to profession, the NCT function of the NetworkComparisonTest package was used under the configuration suggested and predetermined by the developers of the method with 100 iterations for which it was taken into account that if the p-value of the M (global network invariance) and S (global connection degree) statistic is > .05, then there is no statistically significant difference (Van Borkulo, 2015).

RESULTS

Preliminary analysis of variables

Table 2 shows the descriptive statistics of the variables for each group, where it is observed that there are higher PF (M = 12.62; TD = 6.71) and EE (M = 10.80; TD = 5.57) scores in physicians; while the hours of sleep and depression scores are similar in both groups. In addition, kurtosis and asymmetry values indicate non-normality, as they exceed the recommended ±1.5.

Table 2

Descriptive statistics of variables by profession

	Total				Medicine				Nursing			
	M	DT	g1	g2	M	DT	g1	g2	M	DT	g1	g2
EE	11.59	6.16	1.18	0.88	12.62	6.71	0.94	0.13	10.80	5.57	1.36	1.67
DE	8.84	4.67	1.62	2.48	9.86	5.31	1.31	1.13	8.06	3.93	1.84	3.80
PF	31.98	3.72	-1.92	5.27	31.96	3.65	-1.94	5.34	31.99	3.76	-1.91	5.22
Dep	2.45	0.88	2.33	6.35	2.47	0.91	2.35	6.47	2.44	0.86	2.29	6.15
HdS	6.63	1.10	0.19	0.37	6.33	1.06	0.42	1.68	6.87	1.06	0.05	-0.20

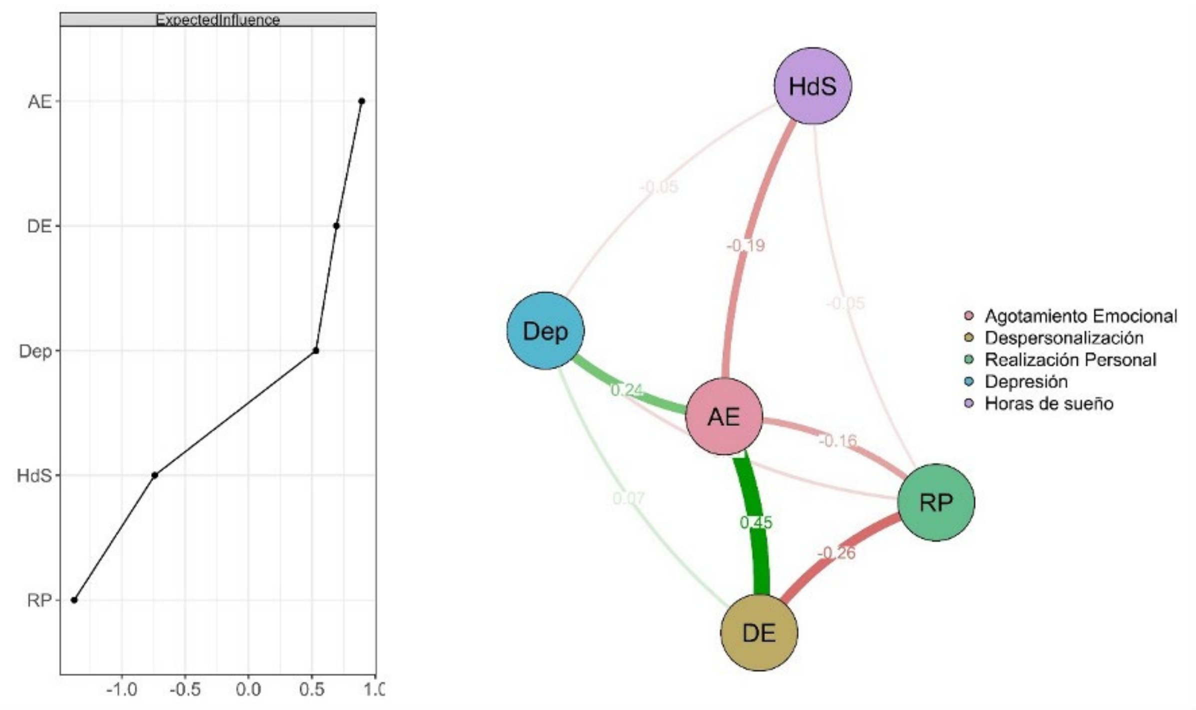
Note: M = arithmetic mean; DT = typical deviation; g1 = skewness; g2 = kurtosis; EE = emotional exhaustion; DE = depersonalization; PF = personal fulfillment; Dep = depression; HS = hours of sleep.

Network analysis

The network for the general population is shown in Figure 1, where a high correlation is observed between EE and SD, which are part of the same construct. In addition, it is noteworthy that depression has a direct and moderate correlation with EE. Likewise, an inverse correlation was found between hours of sleep and EE. On the other hand, the lowest correlations were found between hours of sleep, depression and PF. Regarding the centrality of the network, it is observed that EC is the most relevant node. Therefore, an increase in sleep hours and adequate attention to depressive symptoms could decrease EE.

Figure 1

Network and centrality index in the total Sample



Network stability and accuracy

Figure 2 shows that the network and edges are robust, since a stability coefficient > .50 (CS = .75) was found. Therefore, it is concluded that the network does not vary over the 1000 re-samples.

Figure 2

Network stability and accuracy Comparison of networks according to profession

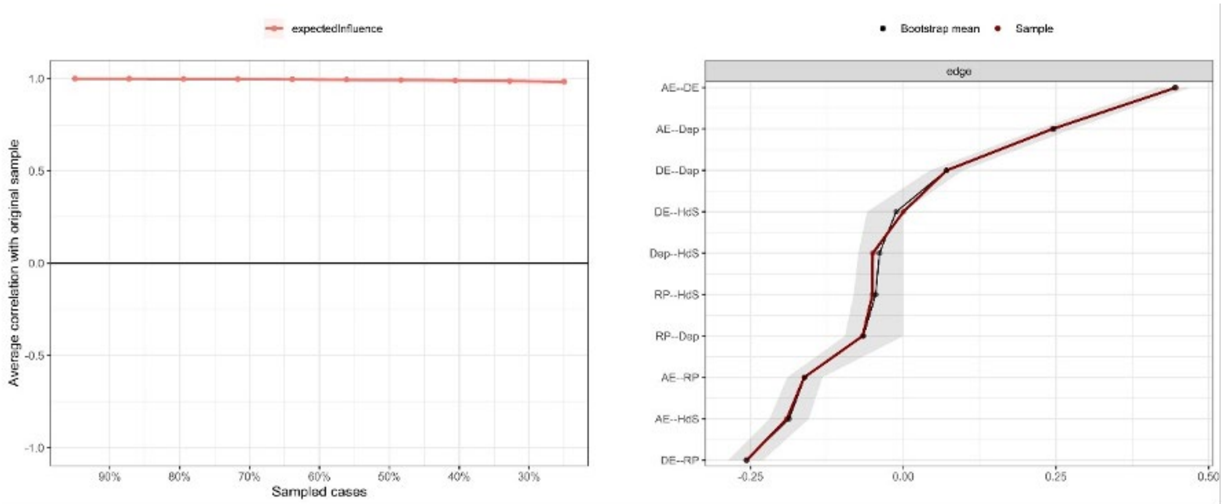
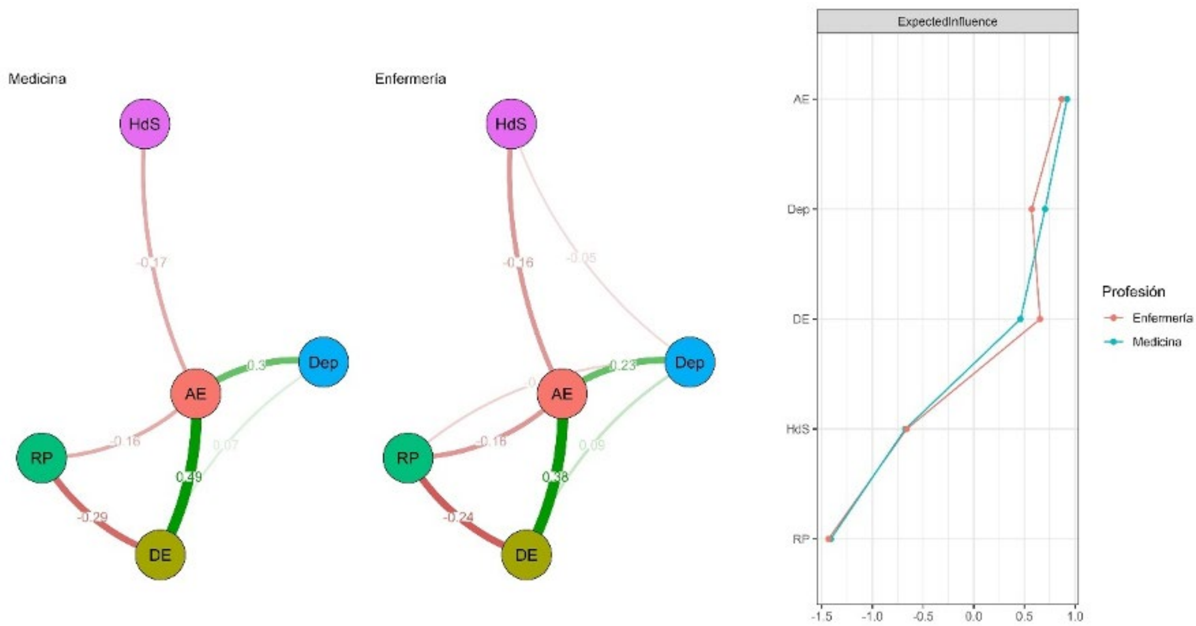


Figure 3 shows the comparison of the networks. Overall, the networks are invariant (M = .11; p = .05) as is the connectivity between nodes (S = .11; p = .31). Similarly, when the correlation between the networks is analyzed, a correlation of r = .97 is obtained. However, when the nodes are examined, it is observed that the hours of sleep have a slight influence on depression in nursing personnel, but not in physicians. In addition, the correlation between EE, SD and depression is stronger in medical staff. It seems that there is a greater interaction between the nodes in nurses.

With respect to centrality, it is observed that EE is the most influential node in physicians, as is depression. However, EE and DE are more relevant in nurses.

Figure 3

Comparison of networks and centrality index in physicians and nurses.



DISCUSSION

Health professionals are usually those who present greater work stress due to the nature of their work (Carrillo-Esper *et al.*, 2012), therefore, it is common for doctors and nurses to have high levels of BO and among some associated factors are sleep hours and depression (Stewart & Arora, 2019; Weaver *et al.*, 2020). This study is the first to examine the relationships of the three components of BO, depression, and sleep hours in nursing and medical professionals in Peru using network analysis. From this perspective, partial correlations among the variables were examined by controlling for the influence of each of them on the other nodes (Epskamp & Fried, 2018).

The findings showed that the components of the BO were correlated with each other, which is to be expected because they are part of the same construct (Maslach *et al.*, 2001, 2008). However, the relationship between EE, depression and hours of sleep is striking. These results have also been found in previous studies (Nezkusilova *et al.*, 2020; Tokac & Razon, 2021; Verkuilen *et al.*, 2021), which could indicate that in order to decrease BO, sleep hours should be increased and depressive symptoms should be addressed in a timely manner, both in physicians and nurses. This can be explained by the fact that both medical and nursing staff work rotating and extended hours, which causes a change in the circadian rhythm regarding their sleep hours, generating exhaustion (Stewart & Arora, 2019). This, coupled with caffeine consumption used to mitigate sleep can result in sleep disorders, thus increasing the likelihood of onset of depressive symptoms (Steiger & Pawlowski, 2019; Stewart & Arora, 2019).

Regarding centrality in this network, the analysis indicated that the EE is the most relevant node, which has been reported in educational personnel (Verkuilen *et al.*, 2021). Therefore, these findings are also replicated in health care workers. In addition, there is a significant correlation and closeness between EE and depression, which is why it has come to be claimed that BO is an expression of depression in workers (Nezkusilova *et al.*, 2020). This makes sense when considering that the characteristic of BO is emotional exhaustion that is closely linked to symptoms of depression, such as loss of energy or sleep disturbances (Nezkusilova *et al.*, 2020; Verkuilen *et al.*, 2021). Such results could be due to the fact that the emotional exhaustion experienced by health care workers may be amplified by the nature of their work, as they usually face highly stressful situations such as work pressure, long working hours and frequent contact with the suffering of their patients, which implies greater emotional exhaustion (García-Iglesias *et al.*, 2021; López-López *et al.,* 2019). Moreover, similar to what happens with health personnel in China, in Peru it has been found that depression is linked to emotional exhaustion which again reinforces the idea that personnel who are exposed to constant stress in hospital or clinical contexts are more likely to develop depression (Zhang *et al.*, 2024).

Regarding the comparison between professions, despite the invariance of the networks, a greater interaction of the nodes was found in nursing personnel. On this point, it is noteworthy that depression is related to PF and hours of sleep in those nurses, although the associations are very low. This is probably due to the fact that in nursing they spend more time and, therefore, have more direct contact with patients, which causes compassion fatigue (Pradas-Hernández *et al.*, 2018; Tokac & Razon, 2021); in fact, it has been reported that 69 % of nurses indicate that they do not have enough time to recover emotionally from sensitive and traumatic events (Adriaenssens *et al.*, 2015), which is consistent with that reported by Zhang *et al.* (2024), who found that nursing professionals were more likely to become emotionally destabilized in contrast to the medical profession. Consequently, the bidirectional correlation between PF, depression and hours of sleep, although small, would indicate that the lack of sleep produced mainly by working hours and rotating shifts would affect optimal performance, which would negatively impact the perception of professional/personal achievement increasing vulnerability to depression (Aryankhesal *et al.*, 2019; Chen & Meier, 2021; Edward *et al.*, 2014; Melnyk, 2020). Therefore, it is important to promote working conditions in which nurses can have regular shifts in order to reduce the effects of fatigue due to the few hours dedicated to sleep, as these have been found to be predictors of depression (Weaver *et al.*, 2020).

In addition, it was found that in both nursing and medical staff, EA and depression were the nodes with the highest centrality, which coincides with previous research where both have shown greater relevance, even when associated with other variables such as anxiety or stress (Fischer *et al.*, 2020; Nezkusilova *et al.*, 2020; Verkuilen *et al.*, 2021). This can be explained due to the fact that healthcare personnel, mainly physicians and nurses, have the highest prevalence of BO (Adriaenssens *et al.*, 2015; Cobo *et al.*, 2019; Monsalve-Reyes *et al.*, 2018; Pradas-Hernández *et al.,* 2018; Rezaei *et al.*, 2018; Rotenstein *et al.*, 2018; Trujillo *et al.*, 2020) since they often encounter adverse events, such as the death of their patients which directly affect their well-being, both physically and psychologically, which would trigger depression or anxiety due to the sensitive nature of these situations (Aryankhesal *et al.*, 2019; Melnyk, 2020).

Despite the interesting results, this study has some limitations, such as having followed a cross-sectional design, which prevents us from knowing the interaction of the nodes over time. Furthermore, as this is a secondary analysis, the exact procedure for administering the instruments is unknown, which could affect the scores obtained. Similarly, not having a defined internal structure of the MBI-HSS for the two populations could affect the measurement because there is a risk that the indicators of the instrument do not capture with the same quality each of the dimensions of the BO. Therefore, comparability could be limited. It is also important to note that data collection with a self-report instrument is not free of biases such as social desirability. In this sense, it is recommended that future studies can overcome these disadvantages and establish a solid and invariant internal structure according to profession, as well as triangulate the information obtained from the tests with other sources or objective measures in order to mitigate biases and obtain information from organizational records or third party evaluations in order to obtain other indicators of burnout or depression (e.g. absenteeism, physiological evaluations, behavioral changes reported by family/friends).

However, among the strengths of the research, we can mention that it is a random and nationally representative sample. Therefore, the results can be generalized to physicians and nurses in Peru. In addition, the findings have practical implications. They can be used to implement policies that modify working conditions and strategies to prevent burnout (BO) in healthcare professionals. They can also be used to promote a culture of care and support for this population. This would benefit individuals by improving their well-being and work-life balance. It would also benefit institutions and society by reducing psychosocial risks and improving the quality of patient care.

CONCLUSIONS

In conclusion, emotional exhaustion (EE) and depersonalization (DE) were the nodes with the greatest centrality in the overall network. However, when differentiating by profession, it was observed that in medical personnel the most relevant aspects were EE and depression, while in nursing personnel they were EE and DE, with greater interaction between the nodes in the latter group. Likewise, an inverse relationship was identified between hours of sleep and EE, suggesting that increasing the hours of rest could help mitigate emotional fatigue in healthcare personnel. These findings highlight the importance of implementing strategies to optimize work schedules and improve sleep hygiene in physicians and nurses. Future studies could explore interventions aimed at reducing burnout in healthcare personnel, considering factors such as shift organization and psychosocial support in the hospital setting.

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