Article

Unemployment, Inequality, and Occupational Stress: Mental Health Outcomes in Brazil (2012–2022)

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ABSTRACT: This study examines the relationship between occupational stress-related leaves, classified under International Classification of Diseases code F43, and socioeconomic factors such as unemployment, income inequality, and worker income in Brazil from 2012 to 2022. Work-related stress disorders, especially those involving severe stress reactions and adjustment disorders, are big problems for occupational health. Bad working conditions and differences in income can make these problems worse. This research utilized secondary data from official Brazilian databases to perform time-series analyses and structural equation modeling. Results revealed a decline in stress-related leaves during the COVID-19 pandemic, likely influenced by remote work adoption and reduced exposure to workplace hazards. Structural modeling identified key relationships: unemployment rates and occupational risk exposure were positively associated with stress-related leaves, while higher income levels were protective. Unexpectedly, income inequality influenced aggression-related leaves but had no significant direct impact on stress-related leaves. These findings underscore the multifaceted impact of socioeconomic and workplace factors on occupational health, highlighting the need for policies addressing mental health at work and fostering equitable labor conditions. The study also identifies limitations, including potential underreporting and the exclusion of demographic nuances. Future research should adopt a multidisciplinary approach and consider disaggregated data to enhance understanding and intervention strategies.

Keywords: Occupational stress; Socioeconomic factors; Workplace mental health; Unemployment; Income inequality; Health and safety at work

1. Introduction

Work-related mental disorders represent a growing challenge, particularly in contexts of intense work pressures, adverse conditions, and increasing social tension [1,2]. The impact of these conditions is exacerbated by the precarization of labor relations, including temporary contracts, exhausting working hours, and organizational practices prioritizing results over workers' well-being [3–6], especially in countries where social and economic instability are prevalent, such as Brazil [7,8].

In Brazil, when recognized as a work-related illness, mental disorders can be equated to occupational accidents [9,10]. This equivalence serves as an important protective mechanism, ensuring workers access to occupational benefits and the possibility of leave with social security support [1]. In this context, "work leave" refers to the temporary absence from work due to a health condition that prevents the employee from performing their regular duties. When a mental disorder is recognized as work-related, it is classified as an occupational disease or deemed equivalent to a work-related accident [1]. This classification is essential because it enables the worker to access specific social security benefits, such as leave due to work-related illness and accident insurance. These benefits ensure financial support during the period of absence while the worker receives appropriate treatment. Additionally, including these cases in official databases facilitates the monitoring of their incidence and progression over time.

Among work-related mental disorders, stress-centered conditions occupy a prominent position. The work environment can amplify risk factors such as overload, tight deadlines, job instability, and interpersonal conflicts [2,11].

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Consequently, stress-related disorders emerge as paradigmatic examples of the adverse consequences of dysfunctional work environments, linking broader social demands to the direct impact on workers' mental health [4].

Stress-related disorders, particularly those classified under International Classification of Diseases (ICD F43), such as Severe Stress Reactions and Adjustment Disorders, exemplify the consequences of work-related pressure [4]. These diagnoses range from acute stress episodes to chronic difficulties in adapting to changes or adversities [4,12], often related to factors such as workplace bullying, work overload, and lack of professional recognition [2].

The ICD F43 category, which includes Post-Traumatic Stress Disorder (PTSD) and Adjustment Disorders, is particularly relevant in the context of work-related illnesses. PTSD, for instance, can arise in workers exposed to traumatic events, such as severe accidents, workplace violence, or disasters [13]. Symptoms include reliving the event, hypervigilance, and avoidance of trauma-associated situations [14]. Meanwhile, Adjustment Disorders reflect difficulties in coping with changes or adverse conditions, such as organizational restructuring, mass layoffs, or interpersonal conflicts [15,16].

Factors associated with ICD F43 include both organizational and individual elements. Excessive pressure for results, intense work rhythms, unhealthy or hazardous environments, poor interpersonal relationships, and exposure to bullying or violence are recurring factors [12]. In some cases, the interaction of these factors leads to chronic stress, affecting not only mental health but also workers' quality of life and productivity [4,11,12]. These factors are also closely linked to conditions described in other ICD categories, such as exposure to violence and aggression (X85–Y09) and exposure to occupational risk factors (Z57).

Contextually, unemployment and inequality are socioeconomic factors with a significant impact on workers' mental health, affecting both those who directly face these conditions and those living under the threat or pressure they create [3,7,8]. These elements interact in complex ways with labor conditions, financial stability, and psychological well-being, contributing to increased vulnerability to mental disorders.

Unemployment, often associated with insecurity, loss of professional identity, and financial difficulties, can trigger or exacerbate anxiety, depression, and stress, affecting psychological and social well-being [17,18]. Work, in addition to providing sustenance, offers purpose and belonging, and its absence can lead to feelings of uselessness, social isolation, and low self-esteem [17,19]. The pressure to compete for new opportunities in a challenging job market heightens these effects, especially in contexts of high unemployment rates. Simultaneously, inequality and disparities in wages and social status deepen tensions among workers, generating perceptions of injustice and devaluation that often result in psychological distress [6,20–22]. In this scenario, income levels play a protective role, as better economic conditions can mitigate negative impacts, providing greater stability and access to resources that promote mental health and well-being [23–26].

Given this scenario, it becomes essential to deepen the understanding of how labor, social, and economic factors interact to influence workers' mental health. Thus, social security records of leave due to stress-related occupational conditions are fundamental tools for this analysis, as they provide objective and systematized data on the incidence of these conditions in the work context. Additionally, these records enable the analysis of relationships with socioeconomic indicators, such as unemployment rates, inequality, and income levels.

In this context, this study aimed to analyze the relationships between leaves due to occupational stress, classified under ICD F43, and social factors such as unemployment rates, inequality, and workers' income based on official indicators. Furthermore, it seeks to investigate the interaction between different occurrences of ICD categories, such as exposure.

Hypotheses

(1) H1—Leaves Due to Stress (LS):
   a. H1.1—Unemployment (U) increases LS, as a significant source of stress.
   b. H1.2—Inequality (I) increases LS, due to the psychological impact of inequality.
   c. H1.3—Income (I) reduces LS, as it protects mental health in prosperous scenarios.
   d. H1.4—Aggression (A) and Occupational Risks (OR) increase LS, due to the psychological impacts of violence and work insecurity.

(2) H2—Leaves Due to Aggression (A):

a. H2.1—Unemployment (U) increases A, due to the psychological and social impact of unemployment.
b. H2.2—Inequality (I) increases A, due to social tensions related to inequality.
c. H2.3—Income (I) reduces A, due to better economic conditions.

(3) H3—Leaves Due to Exposure to Occupational Risks (OR):

a. H3.1—Unemployment (U) reduces OR, due to decreased activities in risk sectors during periods of high unemployment.
b. H3.2—Inequality (I) increases OR, due to poorer working conditions in unequal contexts.
c. H3.3—Income (I) reduces OR, due to increased investments in occupational safety.

2. Materials and Methods

The study employs an exploratory method, analyzing secondary data obtained from public databases.

2.1. Databases

2.1.1. AEPS InfoLogo

A system that enables access and customization of tables based on data from the Statistical Yearbook of Social Security (AEPS), an official report by the Brazilian government that provides detailed information on social security, including welfare and occupational benefits [27]. The AEPS is produced by the Ministry of Social Security, offering a comprehensive and structured database on the dynamics of granting benefits related to illnesses, work accidents, and occupational leaves.

2.1.2. SIDRA (Sistema IBGE de Recuperação Automática—IBGE Automatic Recovery System)

A platform by the Brazilian Institute of Geography and Statistics (IBGE) used to access social indicators such as the Gini Index (income inequality) and the real monthly income of workers [28]. The Gini Index was selected as it is a measure of inequality that evaluates income distribution within a population [29]. It ranges from 0 to 1, where 0 represents complete equality (everyone has the same income), and 1 represents maximum inequality (a single person holds all income) [30]. In this study, the Gini Index was used to represent income inequality in Brazil.

2.1.3. PNAD (Pesquisa Nacional por Amostra de Domicílios—National Household Sample Survey)

This source was used to obtain data on unemployment rates in Brazil between 2012 and 2022 [31]. The PNAD is a survey conducted by IBGE to collect detailed information on the socioeconomic characteristics of the Brazilian population. Conducted periodically, the PNAD includes data that allow analyses on topics such as employment, income, education, migration, housing, and access to public services. For this study, the PNAD provided data on unemployment rates, a key indicator for understanding the state of Brazil's labor market. The unemployment rate reflects the proportion of economically active individuals who are unemployed, and its variation over time can indicate changes in labor market stability and worker vulnerability.

The databases used for this study did not allow for the disaggregation of data by demographic characteristics such as gender, age, or profession. Table 1 summarizes the data sources utilized in this study and specifies the corresponding variables obtained from each database.

Table 1. Data Sources and Variables.

Database	Data
AEPS InfoLogo	Work leave data by ICD, by year
SIDRA	Gini Index, by year Monthly and annual Income rates
PNAD	Monthly and annual unemployment rates

2.2. Procedures

The data were extracted from the aforementioned databases and organized into a single repository, integrating information on occupational stress-related leaves (AEPS InfoLogo), income inequality and wage mass (SIDRA), and unemployment rates (PNAD). The systematization ensured temporal consistency and comparability of variables across the years 2012 to 2022.

2.3. Data Analysis

A non-parametric time series analysis was employed to identify trends in the data. Mann-Kendall and Sen's Slope tests, implemented in R using the "trend" package, were applied to verify monotonic changes over the analyzed period. The Mann-Kendall test is a non-parametric method used to identify monotonic trends in time series, assessing whether the series' values show consistent increases or decreases over time [32]. It is particularly suitable for short series and data that do not meet normality assumptions. Results include a coefficient (S), indicating the trend's direction (positive for an increase, negative for a decrease), and a *p*-value to verify statistical significance ($p < 0.05$ indicates a significant trend).

The Sen's Slope estimator complements the Mann-Kendall test by providing an estimate of the trend's slope, representing the rate of change over time [33]. It is robust to outliers and calculates the median of the slopes between all observation pairs. A positive value indicates an increasing trend, while a negative value indicates a decreasing trend in the analyzed variable. These methods were chosen for their robustness in time series analysis, as they are unaffected by strict normality assumptions, providing reliable results within this study's context.

To evaluate the relationship between socioeconomic factors (income inequality, wages, and unemployment rates) and occupational stress-related leaves, Structural Equation Modeling (SEM) was used. This approach allows for simultaneous analysis of multiple relationships between observed and latent variables, integrating different sources of variability into a single theoretical model. The Weighted Least Square Mean and Variance Adjusted (WLSMV) method was employed as the main estimator, considering potential deviations from multivariate normality in the data [34].

Model quality was assessed using fit indices such as chi-square ($\chi2$), which measures the global fit of the model by comparing observed and expected data; ideally, it should not be statistically significant [35,36]. Additionally, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were calculated, with values above 0.90 indicating satisfactory fit [37,38]. The Root Mean Square Error of Approximation (RMSEA) was used to assess the average discrepancy per degree of freedom [39], while the Standardized Root Mean Square Residual (SRMR) was employed to evaluate the average standardized difference between observed and predicted values [40], with values below 0.08 indicating good fit. These cutoff points were interpreted considering confidence intervals and other psychometric indicators as proposed by McNeish et al. [41]. Estimated coefficients were accompanied by 95% confidence intervals, allowing for evaluation of the precision and statistical significance of modeled relationships.

3. Results

3.1. Descriptive Statistics

Table 2 presents annual data spanning from 2012 to 2022, covering measures related to work leave and key socioeconomic indicators. The work leave figures are further divided into three distinct categories, while the economic indicators include a measure of unemployment, an index reflecting income inequality, and an estimate of the average annual income per worker in Brazilian Reais.

Table 2. Descriptive data.

Year	Work Leave			UR	GI	IR *
	SL	AL	OR			
2012	7892.00	1985.00	2436.00	7.40	0.54	10,661.33
2013	9121.00	1943.00	2630.00	6.30	0.53	11,927.75
2014	9217.00	1770.00	3082.00	4.80	0.53	13,218.67
2015	11,118.00	1836.00	3409.00	6.90	0.52	13,909.67
2016	11,031.00	1810.00	3039.00	9.60	0.54	14,982.00
2017	10,020.00	1947.00	2823.00	12.70	0.54	15,519.67
2018	8807.00	2366.00	2495.00	12.30	0.55	16,731.67
2019	6893.00	2116.00	2370.00	12.20	0.54	17,727.08
2020	3658.00	1408.00	1709.00	11.40	0.52	17,282.08
2021	4084.00	1776.00	1635.00	14.50	0.54	18,120.92
2022	3485.00	2180.00	1612.00	11.20	0.52	21,094.08
Meam	7756.91	1921.55	2476.36	9.94	0.53	15,561.36
SD	2855.50	251.98	612.71	3.14	0.01	3032.33

Note: SL = stress-related leaves; Al = aggression-related leaves; OR = leaves due to occupational risk exposure (OR); UR = unemployment rate; GI = Gini Index; IR = income rate; * = annual income rate per worker, in Reais (BRL).

3.2. Time Series Analysis

The Mann-Kendall test indicated a moderate negative trend in the time series of "Severe Stress Reactions" ($\tau = -0.491$; $p = 0.043$), demonstrating a statistically significant decrease over time. The Sen's Slope estimate pointed to an average annual reduction of approximately 629.63 cases per year. These results suggest a consistent decline in cases of severe stress reactions between 2012 and 2022 (Figure 1).

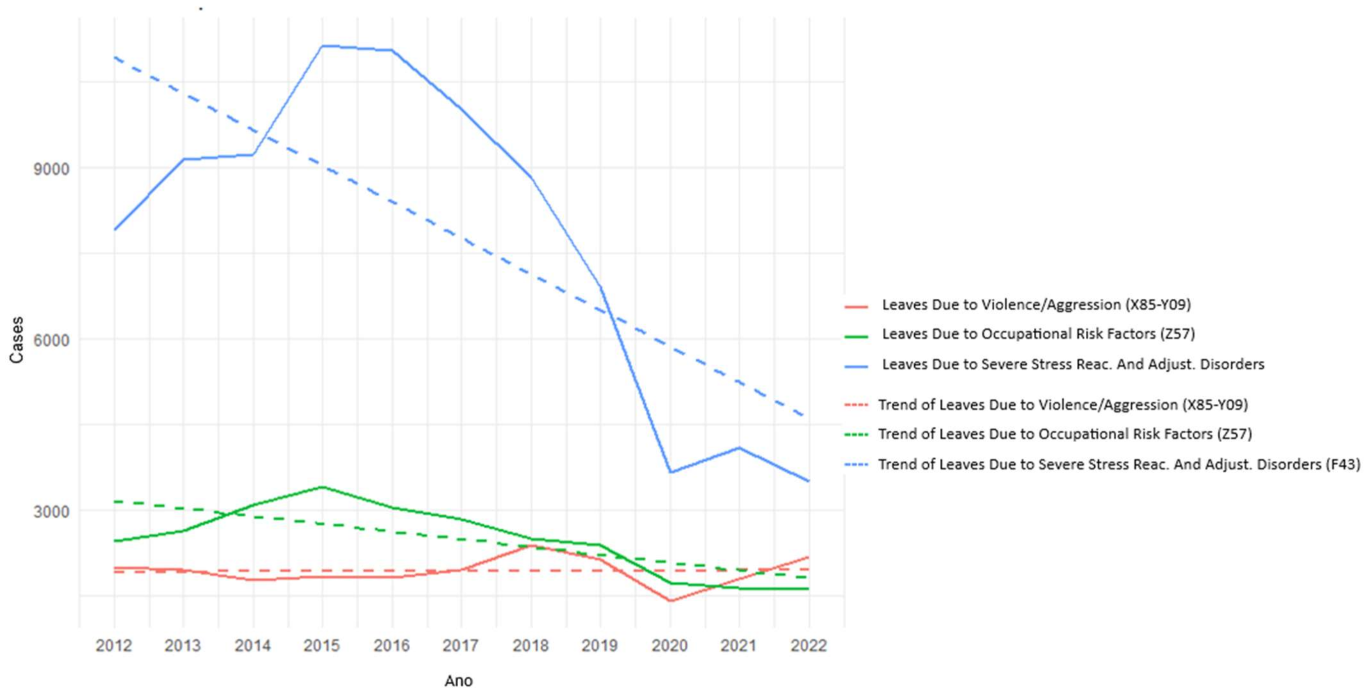

Figure 1. Temporal series and trends.

The trend analysis for the "Aggression" series did not yield significant results. The Mann-Kendall test revealed a slightly positive but insignificant trend ($\tau = 0.054$; $p = 0.876$), while the Sen's Slope estimated an average increase of just one case per year. These results indicate that aggression cases remained relatively stable during the analyzed period.

Results for the "Occupational Exposure to Risk Factors" series showed a strong and statistically significant negative trend. The Mann-Kendall test presented a value of $\tau = -0.600$; $p = 0.013$, and the Sen's Slope estimated an average annual reduction of approximately 146.75 cases per year. This indicates a consistent decrease in occupational exposure cases over the period from 2012 to 2022.

3.3. Structural Equation Modeling

Structural Equation Modeling (SEM) was employed to investigate the relationships between stress-related leaves (SL), aggression-related leaves (AL), leaves due to occupational risk exposure (OR), and socioeconomic factors such as unemployment rate (UR), Gini Index (GI), and income rate (IR) (Figure 2). The fit indices demonstrated excellent model adequacy. The CFI, with a value of 1.000, and the TLI, of 1.221, indicated a perfect fit. The RMSEA presented a value of 0.000, suggesting no significant discrepancies between the model and observed data, while the SRMR of 0.017 revealed minimal discrepancy. Additionally, the chi-square test was non-significant ($p = 0.751$), reinforcing the model's adequacy to the data.

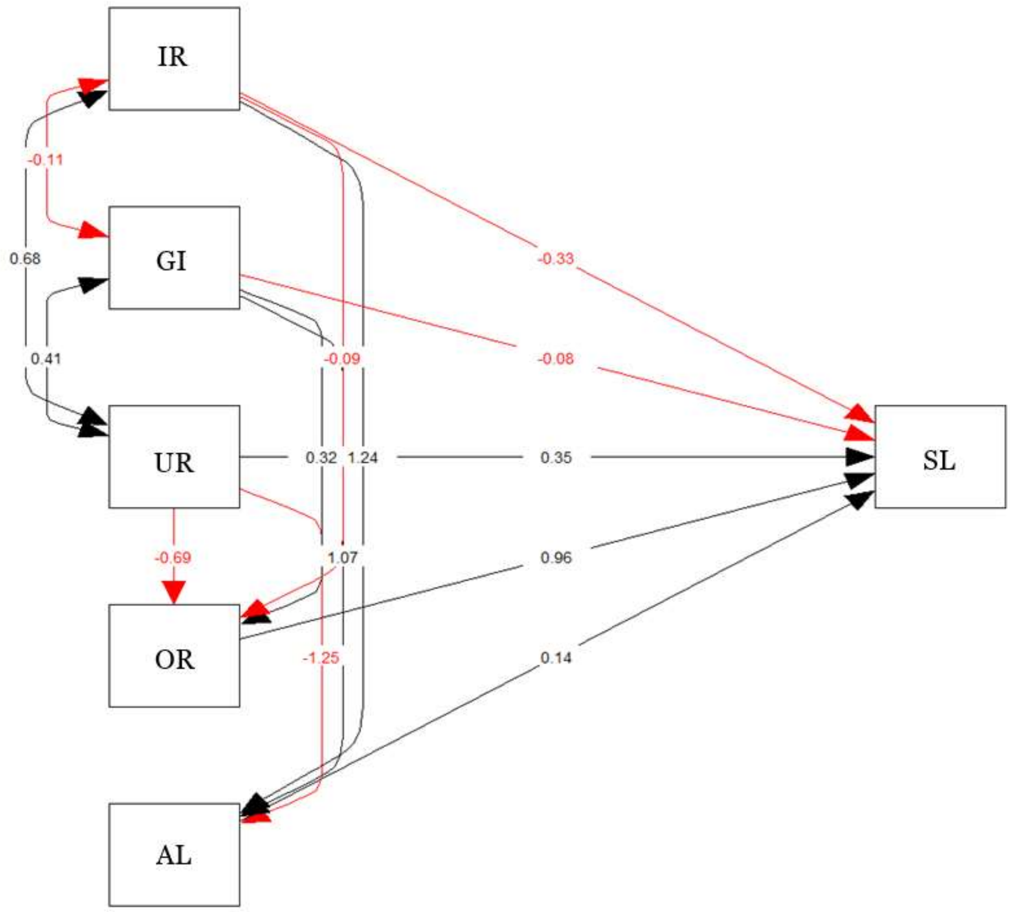

Figure 2. Structural Model. Red arrows indicate negative effects.

The modeling of the backward relationships, where stress-related leave (SL) was used to predict the socioeconomic indicators, yielded coefficients that were essentially zero. These near-zero coefficients indicate that, according to our model and data, stress-related leave does not have a detectable impact on the unemployment rate (UR), the Gini Index (GI), or the income rate (IR).

The regression results indicated significant relationships among the analyzed variables (Table 3). For aggression-related leaves (AL), the unemployment rate (UR) showed a marginally significant negative impact, with a coefficient of −1.25 (p = 0.053), suggesting that increases in unemployment tend to reduce aggression-related leaves. The Gini Index (GI), on the other hand, had a significant positive impact, with a coefficient of 1.069 (p = 0.013), indicating that higher levels of social inequality are associated with increased aggression-related leaves. Income rate (IR) also showed a significant positive impact, with a coefficient of 1.237 (p = 0.033), suggesting that better income levels may be related to increased aggression records.

Table 3. Regressions.

Regression	Estimate	Std.Err.	*z*-Value	*p*-Value	Std.lv	Std.all
AL ← UR	−1.25	0.65	−1.931	0.053	−1.25	−1.25
AL ← GI	1069.00	0.43	2.493	0.013	1069.00	1069.00
AL ← IR	1237.00	0.58	2.128	0.033	1237.00	1237.00
OR ← UR	−0.69	0.59	−1.184	0.236	−0.69	−0.69
OR ← GI	0.32	0.39	0.82	0.411	0.32	0.32
OR ← IR	−0.09	0.53	−0.18	0.860	−0.09	−0.09
SL ← AL	0.14	0.06	2.309	0.021	0.14	0.14
SL ← OR	0.96	0.07	14.527	0.000	0.96	0.97
SL ← UR	0.35	0.16	2.247	0.025	0.35	0.35
SL ← GI	−0.08	0.11	−0.75	0.455	−0.08	−0.08
SL ← IR	−0.33	0.14	−2.405	0.016	−0.33	−0.33

Note: Std.Err. = standard error of the estimate; Std.lv = standardized coefficient at the latent variable level; Std.all = fully standardized coefficient considering all observed variables.

For leaves due to occupational risk exposure (OR), none of the exogenous variables showed statistical significance. Although the unemployment rate (UR) exhibited a negative coefficient, the impact was not significant.

In the case of stress-related leaves (SL), the results showed that aggression-related leaves (AL) had a significant positive impact, with a coefficient of 0.138 ($p = 0.021$). Leaves due to occupational risk exposure (OR) were the main predictor of stress-related leaves, presenting a coefficient of 0.962 ($p < 0.001$). Additionally, the unemployment rate (UR) had a significant positive impact on stress-related leaves, with a coefficient of 0.350 ($p = 0.025$), suggesting that unemployment contributes to an increase in this type of leave. Conversely, the income rate (IR) showed a significant negative impact, with a coefficient of −0.330 ($p = 0.016$), indicating that better economic conditions help reduce stress-related leaves. The Gini Index (GI), however, did not show a significant impact on stress-related leaves.

The model's covariances indicated a significant positive correlation between the unemployment rate (UR) and the income rate (IR), with a coefficient of 0.685 ($p = 0.046$), suggesting that fluctuations in unemployment influence income levels. The relationship between the unemployment rate (UR) and the Gini Index (GI) was marginally significant, with a coefficient of 0.412 ($p = 0.171$). No significant relationship was observed between the Gini Index (GI) and the income rate (IR). The variances for aggression-related leaves (AL), occupational risk exposure leaves (OR), and stress-related leaves (SL) were all statistically significant ($p = 0.019$), indicating that these phenomena have relevant variability partially explained by the factors included in the model.

4. Discussion

4.1. Analysis of Historical Series

The significant negative trend observed in the records of leaves related to severe stress reactions, with an average reduction of 629 cases per year, can be partially explained by changes in the work environment during the pandemic. The widespread adoption of remote work may have contributed to a decrease in stress associated with physical workplace factors, such as long commutes, direct exposure to supervisors, and interpersonal conflicts in corporate settings. However, it is important to consider that this reduction in records may also reflect practical difficulties in accessing health and social security systems during the pandemic, including the interruption of medical examinations at the National Institute of Social Security (INSS), which limited the formal diagnosis and official recognition of these conditions [9,10].

The absence of a significant trend in aggression cases, which remained relatively stable over time, can be explained by the fact that workplace violence dynamics may not have undergone relevant changes in terms of official records despite labor changes. Additionally, this category includes aggression committed by individuals external to the workplace, such as clients and service users, which may have remained stable even during the pandemic [19].

The significant reduction in cases of occupational exposure to risk factors, with an average annual decrease of 147 cases, directly reflects the impact of changes in working conditions during the pandemic. The transition to remote work temporarily eliminated exposure for many workers to hazardous workplace conditions, such as noise, chemical, biological, or ergonomic agents. Moreover, the shutdown of economic sectors, especially industries and in-person services, may have contributed to the decline in the registration of these illnesses. However, the interruption of medical examinations also played an important role, limiting the formal recognition of conditions related to in-person work environments during this period.

The COVID-19 pandemic period brought substantial challenges to monitoring and recording occupational illnesses in Brazil. The temporary suspension of medical examinations by Social Security created a bottleneck in the official recognition of work-related illnesses. Furthermore, the shift to remote work profoundly altered traditional occupational exposures, shifting health risks to new contexts, such as musculoskeletal disorders associated with inadequate remote work setups, emotional stress from isolation, and difficulty reconciling professional and family demands in the same physical space.

It is important to note that while the absolute numbers of occupational illnesses decreased during the analyzed period, these data do not necessarily reflect an improvement in working conditions but rather changes in the dynamics of recording and exposure. The gradual return to in-person activities may reveal a subsequent increase in the registration of these illnesses, especially in categories where risk factors remain high [1].

4.2. Hypothesis Testing

The Structural Equation Modeling (SEM) demonstrated the overall quality of fit, evidenced by the statistical indicators obtained. The CFI (1.00) and TLI (1.22) pointed to an ideal model fit, while the RMSEA (0.000) suggested that the model fits the data. The SRMR (0.017), in turn, indicated a low discrepancy between the observed and estimated data. Additionally, the chi-square test presented a p-value of 0.751, which reinforces the model's adequacy by not rejecting the null hypothesis of good fit. Together, these results indicate that the proposed model is robust and provides a reliable basis for analyzing the formulated hypotheses.

In our study, the backward relationships, where stress-related leave was modeled as a predictor of the socioeconomic indicators, yielded coefficients that were essentially zero. This result suggests that, within our sample and model specification, there is no evidence that stress-related leave exerts an influence on the unemployment rate, the Gini index, or the income rate. Furthermore, the standard errors for these paths were not estimable (reported as NA), indicating potential issues with model identification, possibly due to low variability or redundancy with other components of the model. These findings imply that the causal flow may predominantly operate from socioeconomic conditions toward work-related outcomes, rather than in the reverse direction. Future research should consider alternative model specifications or additional data to further explore and clarify the nature of these bidirectional relationships.

Overall, the hypothesis analysis indicated a combination of confirmations and refutations, reflecting the complexity of the relationships between macroeconomic variables and different types of work-related leaves (Table 4). Hypotheses related to stress-related leaves (SL) showed greater consistency with initial expectations, highlighting the significant impact of Unemployment Rate (UR), Income Rate (IR), and adverse work conditions such as Aggression (AL) and Occupational Risk Exposure (OR). On the other hand, hypotheses concerning aggression-related leaves (AL) and occupational risk exposure leaves (OR) showed more divergent results, with some expected relationships not being confirmed, such as the role of UR and IR in reducing these outcomes. Notably, the Gini Index (GI) showed significant impact in some situations, such as in the increase of AL, but was not relevant for SL or OR, suggesting that social inequality may affect work indirectly or be mediated by other variables. These results underscore the importance of a multifactorial perspective when analyzing the work context, considering not only economic variables but also organizational and cultural factors that influence work dynamics [6,7,24].

Table 4. Hypothesis Analysis.

Hypothesis	Result	Justification
H1.1—UR increases SL	Confirmed	UR had a significant positive impact on SL
H1.2—GI increases SL	Refuted	GI had no significant impact on SL
H1.3—IR reduces SL	Confirmed	IR had a significant negative impact on SL
H1.4—AL and OR increase SL	Confirmed	AL and OR had a significant positive impact on SL
H2.1—UR increases AL	Refuted	UR marginally reduced AL
H2.2—GI increases AL	Confirmed	GI had a significant positive impact on AL
H2.3—IR reduces AL	Refuted	IR had a significant positive impact on AL
H3.1—UR reduces OR	Refuted	UR had no significant impact on OR
H3.2—GI increases OR	Refuted	GI had no significant impact on OR
H3.3—IR reduces OR	Refuted	IR had no significant impact on OR

Regarding stress-related leaves (SL), the results indicate significant relationships that support part of the initial hypotheses. The hypothesis that the Unemployment Rate (UR) increases stress-related leaves was confirmed, demonstrating a significant positive impact. This corroborates the literature that identifies unemployment as one of the main sources of stress, not only due to financial instability but also because of the psychological impact of social vulnerability situations, such as isolation and loss of occupational identity [8,17–19]. Conversely, the Gini Index (GI), despite being an important indicator of social inequality, showed no significant impact on stress-related leaves, refuting the initial hypothesis. This result suggests that while social inequality is relevant in various dimensions of health, its effects may be mediated by contextual variables such as working conditions, social support, and access to mental health services, which dilute its direct impact on occupational stress [22].

The Income Rate (IR), on the other hand, had a significant negative impact on stress-related leaves, confirming the hypothesis that better economic conditions can protect workers against stress by promoting greater stability and psychological security [6,24,26,42].

Stress-related leaves (SL) were significantly predicted by aggression-related leaves (AL) and occupational risk exposure (OR). The findings underscore the critical psychological impact of unsafe working conditions and workplace violence on stress-related outcomes [4–6]. Aggression (AL) showed a positive and significant relationship with SL, suggesting that experiences of interpersonal violence in the workplace contribute directly to elevated stress levels [2,4,12]. Similarly, occupational risk exposure (OR) emerged as the strongest predictor of SL, highlighting the importance of addressing unsafe environments to mitigate stress-related disorders. These results emphasize the interconnectedness of workplace conditions and stress-related outcomes, underlining the need for targeted interventions to promote safety and psychological well-being at work. These findings reinforce the need for targeted interventions to ensure safety and well-being in the workplace [2,4,5].

In terms of aggression-related leaves (AL), the results indicated interesting nuances. The hypothesis that the Unemployment Rate (UR) would increase aggression-related leaves was refuted, with UR showing a marginally negative impact. This finding can be explained by reduced exposure to work environments during periods of high unemployment, as interpersonal interactions decrease due to smaller teams or reduced activities in some organizations. Another possibility is that in unemployment contexts, workers who retain their jobs may adopt a more tolerant stance or avoid reporting aggression for fear of reprisals or losing their positions [19]. Conversely, the hypothesis that the Gini Index (GI) would increase aggression-related leaves was confirmed, showing that social inequality amplifies interpersonal tensions and conflicts, which can result in workplace aggression. Surprisingly, the Income Rate (IR) showed a significant positive impact on aggression-related leaves, refuting the initial hypothesis. This result may indicate that workers in higher-income positions have greater visibility and awareness of their rights, leading them to report aggression more frequently [21–23]. Alternatively, higher income levels may be associated with more competitive work environments, where interpersonal tensions and conflicts, including verbal aggression, are more common.

In the context of occupational risk exposure leaves (OR), none of the hypotheses were confirmed. The Unemployment Rate (UR) had no significant impact, suggesting that high unemployment is not directly related to workplace safety conditions. This result may reflect the maintenance of activities in essential sectors such as construction and mining even in adverse economic scenarios [8]. The hypothesis that the Gini Index (GI) would increase risk exposure leaves was also refuted. This finding points to a more complex relationship between social inequality and unsafe working conditions, possibly mediated by legal regulations and public policies that mitigate the direct effects of inequality. Similarly, the Income Rate (IR) showed no significant impact, contrary to the expectation that better economic conditions would lead to greater investment in occupational safety. One possible explanation is that even in favorable economic contexts, some companies may prioritize profit over workplace safety, especially in sectors with high labor turnover [9].

However, in another context (e.g., European countries), cohort studies conducted in pre-pandemic periods suggest that more subtle or mediated reciprocal relationships might exist between work conditions and occupational stress [43–45]. Even though the present study did not detect significant effects of stress-related leaves on macroeconomic variables, previous findings indicate that deteriorating mental health among employees may, in some cases, prompt or intensify adverse psychosocial conditions at work. Furthermore, an analysis of cross-country differences showed that organizations with clearly defined risk-management policies, including designated roles for dealing with psychosocial stress, tend to have lower levels of psychosocial risk [46]. Such findings suggest that large increases in stress-related absences might encourage companies—particularly in well-regulated environments—to bolster preventive strategies, thereby creating a feedback loop where higher leave rates trigger improvements in health and safety measures.

Thus, while the present results revealed minimal backward effects, other evidence implies that reciprocal influences could emerge more clearly under certain contexts, such as longer follow-up intervals, more detailed data on organizational practices, or when examining smaller units of analysis (e.g., at the company or sector level). When comparing the Brazilian and European contexts, it is important to note that structural and cultural differences may shape these potential feedback loops in distinct ways. In Brazil, where higher informality, underreporting, and economic inequality are prevalent, workers may be more hesitant to seek leaves due to fear of unemployment or job instability [7,17,21]. Additionally, insufficient oversight and limited access to formal occupational health services can mask the actual impact of psychosocial risks. Cultural and organizational factors—such as prioritizing productivity and short-term economic outcomes over employee well-being—may further undermine the implementation of mental health initiatives [11,16,23,24]. These findings emphasize the need for a closer look at the specificities of the Brazilian labor market and the interaction between economic, social, and organizational variables in fostering a safer and healthier work environment.

5. Conclusions

This study provides an analysis of work-related stress disorders in Brazil from 2012 to 2022, highlighting the interplay between macroeconomic factors, occupational conditions, and health outcomes. The findings reveal significant trends, such as the reduction in stress-related leaves during the pandemic and the enduring influence of socioeconomic inequality on workplace aggression. These insights underscore the complexity of labor dynamics in Brazil, particularly in contexts of economic and social instability.

One major limitation of this research is the lack of disaggregated data by sex, ethnicity, and other demographic factors, which restricts the understanding of how these variables may intersect with occupational stress. Additionally, the reliance on official records might overlook underreported cases, particularly in informal or poorly monitored sectors. The disruption of medical evaluations during the COVID-19 pandemic further complicates the interpretation of trends, as it likely affected the accuracy of official statistics.

Future research should prioritize collecting and analyzing disaggregated data to explore the differential impacts of occupational stress across diverse groups. Moreover, interdisciplinary approaches integrating organizational psychology, public health, and labor economics can offer a more comprehensive understanding of how structural inequalities influence workplace well-being.

From a practical perspective, the findings emphasize the need for targeted policies to address workplace safety, mental health support, and the mitigation of socioeconomic inequalities. Employers and policymakers should consider proactive measures to reduce occupational stressors, foster equitable work environments, and enhance support systems for workers across all sectors. These actions are crucial for promoting healthier, more sustainable labor practices in Brazil and beyond.

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Ethics Statement

This study relied exclusively on secondary data from public sources which provide aggregated, non-identifiable information. As these datasets are publicly available and contain no personal or sensitive details, the research complied with ethical standards without requiring individual consent. The study adhered to regulations governing research in Brazil, which allow the use of public data with no associated risks to participants. The data were used solely for scientific purposes to analyze the relationship between socioeconomic factors and occupational stress-related leaves. Results are presented responsibly, ensuring data integrity and avoiding stigmatization of any groups or individuals.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data utilized in this study were obtained from publicly available databases. These datasets are openly accessible and can be retrieved following the respective database guidelines and terms of use. The access links are provided in the article's references.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Mendonça PBDS, Costa IB, Costa VCDGESFD, Castro JLD. Leave due to mental disorders in workers in the Brazilian Northeast: an ecological study. *Rev. Bras. Med. Trab.* **2023**, *5*, e20221007.
2. Rodrigues CML, Faiad C, Facas EP. Fatores de Risco e Riscos Psicossociais no Trabalho: Definição e Implicações. *Psicol. Teor. E Pesqui.* **2020**, *36*, e36nspe19.
3. Belloni M, Carrino L, Meschi E. The impact of working conditions on mental health: Novel evidence from the UK. *Labour Econ*. **2022**, *76*, 102176.

4. Hultén AM, Bjerkeli P, Holmgren K. Work-related stress and future sick leave in a working population seeking care at primary health care centres: a prospective longitudinal study using the WSQ. *BMC Public Health* **2022**, *22*, 851.
5. Rugulies R, Aust B, Greiner BA, Arensman E, Kawakami N, LaMontagne AD, et al. Work-related causes of mental health conditions and interventions for their improvement in workplaces. *Lancet* **2023**, *402*, 1368–1381.
6. Vives A, Amable M, Ferrer M, Moncada S, Llorens C, Muntaner C, et al. Employment Precariousness and Poor Mental Health: Evidence from Spain on a New Social Determinant of Health. *J. Environ. Public Health* **2013**, *1*, 1–10.
7. Kortum E, Leka S, Cox T. Psychosocial risks and work-related stress in developing countries: health impact, priorities, barriers and solutions. *Int. J. Occup. Med. Environ. Health* **2010,** *23*, 225–238.
8. Abramson B, Boerma J, Tsyvinski A. Macroeconomics of Mental Health. Available online: https://www.ssrn.com/abstract=4793015 (accessed on 10 November 2024).
9. Rodrigues CML. Saúde mental e trabalho: uma análise dos auxílios-doença acidentários concedidos de 2010 a 2017. *Rev. Psicol. E Conex.* **2018**, *1*, 1–17.
10. Carvalho CADS, Silva JCD, Lima JLLPCD, Brum SDS. Health and Safety at Work: a portrait of occupational accident and disease numbers in Brazil (2012-2018). *Braz. J. Bus.* **2020**, *2*, 2909–2926.
11. Kopp MS, Stauder A, Purebl G, Janszky I, Skrabski A. Work stress and mental health in a changing society. *Eur. J. Public Health* **2008**, *18*, 238–244.
12. Brewin CR, Cloitre M, Chow AYM, Maercker A. Disorders specifically associated with stress. In *A Psychological Approach to Diagnosis: Using the ICD-11 as a Framework*; Reed GM, Ritchie PLJ, Maercker A, Rebello TJ, Eds.; American Psychological Association: Washington, DC, USA, 2024; pp. 175–192.
13. American Psychiatric Association, organizador. *Diagnostic and Statistical Manual of Mental Disorders: DSM-5-TRTM,* Fifth ed.; American Psychiatric Association Publishing: Washington, DC, USA, 2022.
14. World Health Organization. *International Statistical Classification of Diseases and Related Health Problems 10th Revision*; World Health Organization: Geneva, Switzerland, 2009.
15. World Health Organization. *The ICD-10 Classification of Mental and Behavioural Disorders: Clinical Descriptions and Diagnostic Guidelines*, Reprinted ed.; World Health Organization: Geneva, Switzerland, 2010.
16. World Health Organization. *WHO Guidelines on Mental Health at Work*, 1st ed.; World Health Organization: Geneva, Switzerland, 2022.
17. Reichert A, Tauchmann H**.** *The Causal Impact of Fear of Unemployment on Psychological Health*; RWI: Essen, Germany, 2011; p. 23.
18. Burgard SA, Brand JE, House JS. Perceived job insecurity and worker health in the United States. *Soc. Sci. Med.* **2009**, *69*, 777–785.
19. Chirumbolo A, Callea A, Urbini F. The Effect of Job Insecurity and Life Uncertainty on Everyday Consumptions and Broader Life Projects during COVID-19 Pandemic. *Int. J. Environ. Res. Public Health* **2021**, *18*, 5363.
20. Landsbergis PA, Grzywacz JG, LaMontagne AD. Work organization, job insecurity, and occupational health disparities. *Am. J. Ind. Med.* **2014**, *57*, 495–515.
21. Lin Y, Zhang Q, Chen W, Ling L. The social income inequality, social integration and health status of internal migrants in China. *Int. J. Equity Health* **2017**, *16*, 139.
22. Hiilamo H. Is Income Inequality 'Toxic for Mental Health'? An Ecological Study on Municipal Level Risk Factors for Depression. *PLoS ONE* **2014**, *9*, e92775.
23. Kyere E, Fukui S. Structural Racism, Workforce Diversity, and Mental Health Disparities: A Critical Review. *J. Racial Ethn. Health Disparities* **2023**, *10*, 1985–1996.
24. Hannon PA, Harris JR, Doody DR. Opportunities to Improve Health Equity for Employees in Low-Wage Industries in the United States. *Annu. Rev. Public Health* 2**024**, *46*, doi:10.1146/annurev-publhealth-071723-120104.
25. Stack S. Contributing factors to suicide: Political, social, cultural and economic. *Prev. Med.* **2021**, *152*, 106498.
26. Gertner AK, Rotter JS, Shafer PR. Association Between State Minimum Wages and Suicide Rates in the U.S. *Am. J. Prev. Med.* **2019**, *56*, 648–654.
27. Previdência Social. AEPS InfoLogo. 2024. Available online: https://www3.dataprev.gov.br/infologo/inicio.htm (accessed on 23 September 2024).
28. Instituto Brasileiro de Geografia e Estatística. Sistema IBGE de Recuperação Automática—SIDRA [Internet]. 2016. Available online: http://sidra.ibge.gov.br (accessed on 23 September 2024).
29. Gini C. Measurement of Inequality of Incomes. *Econ. J.* **1921**, *31*, 124–126.
30. Farris FA. The Gini Index and Measures of Inequality. *Am. Math. Mon.* **2010**, *117*, 851–864.
31. Instituto Brasileiro de Geografia e Estatística. Pesquisa Nacional por Amostra de Domicílios—PNAD 2024. Available online: https://www.ibge.gov.br/estatisticas/sociais/trabalho/19897-sintese-de-indicadores-pnad2.html (accessed on 23 September 2024).
32. Mann HB. Nonparametric Tests Against Trend. *Econometrica* **1945**, *13*, 245–259.
33. Sen PK. Estimates of the Regression Coefficient Based on Kendall's Tau. *J. Am. Stat. Assoc.* **1968**, *63*, 1379–1389.

34. Beauducel A, Herzberg PY. On the Performance of Maximum Likelihood Versus Means and Variance Adjusted Weighted Least Squares Estimation in CFA. *Struct. Equ. Model. Multidiscip. J.* **2006**, *13*, 186–203.
35. Tanaka JS. "How Big Is Big Enough?": Sample Size and Goodness of Fit in Structural Equation Models with Latent Variables. *Child Dev.* **1987**, *58*, 134–146.
36. West SG, Taylor AB, Wu W. Model fit and model selection in structural Equation Modeling. In *Handbook of Structural Equation Modeling*; Hoyle RH, Organizador; Guilford Press: New York, NY, USA, 2012; pp. 209–231.
37. Bentler PM. Comparative fit indexes in structural models. *Psychol. Bull.* **1990**, *107*, 238–246.
38. Tucker LR, Lewis C. A reliability coefficient for maximum likelihood factor analysis. *Psychometrika* **1973**, *38*, 1–10.
39. Brown TA. *Confirmatory Factor Analysis for Applied Research*; The Guilford Press: New York, NY, USA, 2015.
40. Jöreskog KG, Sörbom D. *LISREL 6: Analysis of Linear Structural Relationships by Maximum Likelihood, Instrumental Variables, and Least Squares Methods; User's Guide*, 4th ed.; Scientific Software, Inc.: Mooresville, CA, USA, 1986.
41. McNeish D, An J, Hancock GR. The Thorny Relation Between Measurement Quality and Fit Index Cutoffs in Latent Variable Models. *J. Pers. Assess.* **2018**, *100*, 43–52.
42. Horn BP, Maclean JC, Strain MR. Do minimum wage increases influence worker health? *Econ. Inq.* **2017**, *55*, 1986–2007.
43. Malard L, Chastang JF, Schütte S, Parent-Thirion A, Vermeylen G, Niedhammer I. Changes in Psychosocial Work Exposures Among Employees Between 2005 and 2010 in 30 Countries in Europe. *J. Occup. Environ. Med.* **2013**, *55*, 1135–1141.
44. Niedhammer I, Chastang JF, Sultan-Taïeb H, Vermeylen G, Parent-Thirion A. Psychosocial work factors and sickness absence in 31 countries in Europe. *Eur. J. Pub. Health* **2013**, *23*, 622–629.
45. Lu YK, Qiao YM, Liang X, Yao W, Yan Z, Wang HX, et al. Reciprocal relationship between psychosocial work stress and quality of life: The role of gender and education from the longitudinal study of the Survey of Health, Ageing and Retirement in Europe. *BMJ Open* **2019**, *9*, e027051.
46. Lunau, T, Nico D, Johannes S, Morten W. Country differences of psychosocial working conditions in Europe: the role of health and safety management practices. *Int. Arch. Occup. Environ. Health* **2017**, *90*, 629–638.