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Application of the AHP-Gaussian method to support the prioritization of workers' health actions in Brazil, based on data from DATASUS

Aplicação do método AHP-Gaussiano para apoio à priorização de ações de saúde do trabalhador no Brasil com base nos dados do DATASUS

Ana Carolina Russo[1], Edison Russo[2]

[1]Universidade de São Paulo – USP, Escola Politécnica, Departamento de Engenharia de Minas e Petróleo, São Paulo, SP, Brasil. E-mail: anacarolinarusso@usp.br

[2]Centro Universitário das Faculdades Metropolitanas Unidas, São Paulo, SP, Brasil. E-mail: erusso@uol.com.br

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Abstract: This study applied the AHP-Gaussian method (AHP-G) to prioritize occupational health actions in Brazil based on data from DATASUS, used to provide analytical approaches needed to manage the complexity and multidimensionality of public health data. Unlike traditional methodologies, AHP-G allows a detailed quantitative analysis, thus mitigating the subjectivity involved in evaluating different criteria. The results indicate that pneumoconiosis and occupational cancer are priorities, with São Paulo emerging as the most critical state. The correlation between population data and the identified priorities highlights the relevance of adjusting public policies to the specific needs of states. This study not only fills a significant gap in the literature by providing a refined analytical tool for policymakers and researchers, but also signals future directions to enhance occupational health strategies in the Brazilian context.

Keywords: Worker`s health; DATASUS; AHP-Gaussian Method.

Resumo: Este estudo aplicou o método AHP-Gaussiano (AHP-G) para priorizar as ações de saúde do trabalhador no Brasil a partir dos dados do DATASUS, utilizado para fornecer abordagens analíticas necessárias para gerenciar a complexidade e a multidimensionalidade dos dados de saúde pública. Diferentemente das metodologias tradicionais, o AHP-G permite uma análise quantitativa detalhada, mitigando a subjetividade envolvida na avaliação de diferentes critérios. Os resultados indicam que pneumoconioses e câncer ocupacional são prioridades, sendo São Paulo o estado mais crítico. A correlação entre os dados populacionais e as prioridades identificadas evidencia a relevância de adequar as políticas públicas às necessidades específicas dos estados. Este estudo não apenas preenche uma lacuna significativa na literatura ao fornecer uma ferramenta analítica refinada para formuladores de políticas e pesquisadores, mas também sinaliza direções futuras para aprimorar estratégias de saúde do trabalhador no contexto brasileiro.

Palavras-chave: Saúde do trabalhador; DATASUS; AHP-Método Gaussiano.

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1 Introduction

Silva et al. (2008) highlight that evidence must be introduced into the governmental decision-making process to best address the inefficient use of public funds. However, the reliability of this evidence is crucial, since inaccurate data can impair the ability of public managers to formulate effective strategies to secure the success of their initiatives.

In this context, it is essential to choose appropriate analytical methods to ensure informed and objective decisions. Among the available methodologies, the analytical hierarchy process Gaussian (AHP-G) method was selected for its ability to minimize the subjectivity of the decision-making process. AHP-G differs from traditional methods, such as AHP, ANP, and Fuzzy AHP, by not having to provide pair-wise comparisons, and adopts a Gaussian distribution-based approach to determine the criterion weights. This choice is warranted by the complexity and quantitative nature of the worker health data furnished by DATASUS, thus providing a tool that promotes objectivity and reduces the risk of bias.

Evidence-based decision-making represents a significant change in the matter of public policies, as described by Cerdeira et al. (2020) and KPMG (2017). This paradigm, known as "data-driven public policies," emphasizes the formulation of programs based on the best available scientific evidence to enhance accuracy, reliability, objectivity, consistency, and transparency in the decision-making process and its implementation (Sherman, 1998; Abt, 2019). Such an approach encourages the selection of alternatives that demonstrate the best performance and evaluation of the decision-maker's expectations, and agreement therewith, thus emphasizing the importance of synergy between the elements (Santos et al., 2015).

Justen & Frota (2018) emphasize that data-based planning and public policies are essential to establish interactions between the federal government, economy, politics, and society, manifested through governmental programs that aim to effect significant changes, improve living conditions, and promote social welfare and development. Thus, data analysis is designed to equip the public sector with the tools that facilitate rapid decision-making, through data processing, analysis, and dissemination within an efficient management system (Handley et al., 2015).

Within this spectrum, multicriteria methods emerge as advantageous solutions, because they allow a more systematic and transparent approach to data taken from complex problems than the data from single-criterion methods (Santos et al., 2015; Souza Marins et al., 2009). The Analytic Hierarchy Process (AHP), for example, is widely used in several fields of knowledge for its effectiveness (Yu et al., 2021).

Specifically in the health sector, the relevance of data is highlighted by the Unified Health System (SUS) established by the Federal Constitution of 1988, and, subsequently, the Department of Information Technology of SUS (DATASUS) in 1991, responsible for maintaining and developing health information systems (Brasil, 1988, 1991, 2002). The mission of DATASUS focuses on the production and dissemination of data, and the establishment of a pillar to support workers' health, an area that has received attention due to its multidisciplinary and interdisciplinary nature (Pinheiro, 1996; Boerma & Stansfield, 2007; Costa et al., 2013; Leão & Castro, 2013).

The focus of the present study was to apply the multicriteria AHP-G method, as developed by Santos et al. (2021), to assist in prioritizing actions aimed at workers' health in Brazil, by using data from DATASUS. This method evolved from the AHP method created by Thomas Saaty (Saaty & Vargas, 2012), and introduces an innovative methodology for analyzing complex and multidimensional data. The implementation of AHP-G not only fills an existing gap in the literature, but also establishes a methodological benchmark for future investigations. This scientific contribution highlights the application of AHP-G as a significant advancement toward providing an objective and quantitative assessment of priorities in public health policies for workers' health. By adapting this approach to the specific context of workers' health, the study not only fills a gap in the literature, but also provides a new tool for researchers and policymakers, thus paving the way for the exploration of other areas of public interest that would benefit from a refined multicriteria decision-making approach (Soares et al., 2021).

2 Material and methods

As described by Silva et al. (2022), the method begins by establishing the decision matrix and its normalization. To this end, the calculations are made based on the following consideration: Let A = {ai| i ∈ I}, |I| = n be the finite set of possible actions or options, and G = {gj| j ∈ J}, |J| = m be the set of criteria evaluated for preference modeling, establishing gj: A → ℝ, ∀j ∈ J as an interval scale measure, such that gj(a) equals action a on the j-th criterion, resulting in the decision matrix.

A classification of action priorities was established to construct the decision matrix, based on seven criteria obtained from the TABNET site of DATASUS, considering the years from 2006 to 2022 (Table 1). The selection of the seven prioritization criteria in this study was guided carefully toward addressing the crucial elements of health and workplace accidents comprehensively and significantly. This choice was grounded on a detailed review of the specialized literature, by weighing the immediate relevance of each criterion to workplace safety, as discussed by Ferrari et al. (2020).

It is crucial to distinguish between occupational diseases and workplace accidents to understand the complexities of the work environment. Occupational diseases emerge due to prolonged exposure to workplace hazards, manifested in conditions such as musculoskeletal disorders, respiratory problems, or noise-induced hearing loss. In contrast, workplace accidents occur suddenly, resulting in immediate injuries or harm, such as falls or exposure to hazardous materials. Occupational diseases are typically progressive, and lead to chronic conditions, while workplace accidents are characterized by their abrupt and immediate nature. Understanding these differences is vital for implementing effective preventive measures, occupational health policies, and risk mitigation strategies.

Each of the selected criteria for the decision matrix has a direct link and significant impact on the health and safety of workers. These criteria reflect crucial influential factors that affect workers both in the event of accident and in the development of occupational diseases. Previous studies emphasize the importance of these aspects, highlighting their relevance and applicability to our study, as noted by Ferrari et al. (2020). Integrating these criteria provides a holistic perspective toward occupational risks, which is essential to undertake a comprehensive and effective study of the field of occupational health and safety, since it ensures our research will address the most relevant and impactful issues, thus contributing to a deeper and more practical understanding of these critical issues.

Table 1. Criteria used 1.

Criteria
Work-related mental disorders
Accidents at work
Occupational accidents with exposure to biological material
Cancer as a function of work
Work-related dermatosis
Work-related hearing loss
Work-related pneumoconiosis

Twenty-seven Brazilian states were considered as alternatives for applying the model (Table 2).

Table 2. Alternatives (states) used for prioritizing actions/campaigns.

	State	
São Paulo	Pará	Santa Catarina
Minas Gerais	Maranhão	Rio Grande do Norte
Paraná	Amazonas	Ceará
Distrito Federal	Sergipe	Pernambuco
Rio Grande do Sul	Rondônia	Tocantins
Mato Grosso do Sul	Roraima	Espírito Santo
Bahia	Piauí	Alagoas
Rio de Janeiro	Amapá	Paraíba
Goiás	Acre	Mato Grosso

Table 3 presents the decision matrix results of the TABNET data analysis for the 7 criteria considered. The calculation was made by assuming the higher the value, the better (max), since the aim was to identify the states that should be prioritized in actions and campaigns for worker health.

Table 3. Decision matrix considering the number of occurrences per state.

State	Mental disorders (max)	Accidents (max)	Accidents with exposure to biological material (max)	Cancer (max)	Dermatosis (max)	Hearing loss (max)	Pneumoconiosis (max)
São Paulo	4,666	477,149	213,983	272	792	2,810	2,333
Minas Gerais	3,112	113,262	103,732	201	1,665	985	1,809
Bahia	1,198	43,134	31,744	33	351	283	201
Rio Grande do Norte	1,150	10,049	14,314	145	46	19	80
Rio Grande do Sul	1,032	112,075	40,242	40	493	986	266
Pernambuco	856	21,157	26,274	8	192	23	68
Paraná	702	117,103	63,604	1,324	364	244	217
Ceará	647	35,352	20,375	48	246	102	34
Alagoas	597	6,447	12,068	79	56	80	6
Mato Grosso do Sul	551	33,164	10,467	537	46	1,126	14
Paraíba	469	17,337	5,946	6	27	29	9
Santa Catarina	407	43,857	37,906	63	100	151	75
Rio de Janeiro	370	29,383	58,687	71	340	532	125
Tocantins	213	19,499	7,603	9	442	23	29
Pará	191	8,306	8,814	21	51	4	15
Amazonas	158	9,964	11,656	0	51	13	13
Sergipe	134	3,475	6,306	5	31	98	3
Goiás	111	54,790	28,961	80	30	1,060	113
Maranhão	89	19,233	9,219	3	33	36	4
Espírito Santo	79	4,655	10,269	1	359	22	127
Rondônia	75	16,864	3,418	8	47	7	5
Distrito Federal	62	12,303	8,802	386	2,420	485	10
Mato Grosso	57	25,320	9,781	6	59	11	13
Roraima	34	10,903	2,915	1	19	2	8
Acre	8	5,510	1,766	0	8	2	0
Piauí	5	9,424	5,780	0	6	1	6
Amapá	1	8,382	1,881	0	30	1	0

Next, the matrix must be normalized to resize the gj(ai) ∀j ∈ J variables to a common range between 0 and 1, and thus retain the values independent of the width of the measurement scale (Greco, 1997). After applying Equations 1 and 2 to the decision matrix, a normalized chj value can be obtained, thus creating a new matrix. While Equation 1 should be used when the criterion has a maximizing behavior (the more the better), Equation 2 should be used when the criterion has a minimizing behavior (the less the better).

$$\frac{a_{ij}}{\sum_i a_{ij}} \forall Maxg_i \tag{1}$$

$$\frac{a_{ij}}{\sum_i a_{ij}} \forall Ming_i \tag{2}$$

After the decision matrix has been obtained (Table 3), the next step is to normalize the values (Table 4).

Table 4. Normalized Decision Matrix.

State	Mental disorders (max)	Accidents (max)	Accidents with exposure to biological material (max)	Cancer (max)	Dermatosis (max)	Hearing loss (max)	Pneumoconiosis (max)
São Paulo	0.274891	0.376272	0.282854	0.081267	0.095376	0.307608	0.417876
Minas Gerais	0.183339	0.089317	0.137119	0.060054	0.200506	0.107827	0.324019
Bahia	0.070579	0.034015	0.041961	0.00986	0.042269	0.03098	0.036002
Rio Grande do Norte	0.067751	0.007924	0.018921	0.043322	0.005539	0.00208	0.014329
Rio Grande do Sul	0.060799	0.08838	0.053194	0.011951	0.059369	0.107937	0.047645
Pernambuco	0.05043	0.016684	0.03473	0.00239	0.023121	0.002518	0.01218
Paraná	0.041357	0.092345	0.084075	0.395578	0.043834	0.02671	0.038868
Ceará	0.038117	0.027878	0.026933	0.014341	0.029624	0.011166	0.00609
Alagoas	0.035171	0.005084	0.015952	0.023603	0.006744	0.008758	0.001075
Mato Grosso do Sul	0.032461	0.026153	0.013836	0.160442	0.005539	0.123262	0.002508
Paraíba	0.02763	0.013672	0.00786	0.001793	0.003251	0.003175	0.001612
Santa Catarina	0.023978	0A.034585	0.050106	0.018823	0.012042	0.01653	0.013434
Rio de Janeiro	0.021798	0.023171	0.077576	0.021213	0.040944	0.058238	0.022389
Tocantins	0.012549	0.015377	0.01005	0.002689	0.053227	0.002518	0.005194
Pará	0.011253	0.00655	0.011651	0.006274	0.006142	0.000438	0.002687
Amazonas	0.009308	0.007857	0.015408	0	0.006142	0.001423	0.002328
Sergipe	0.007894	0.00274	0.008336	0.001494	0.003733	0.010728	0.000537
Goiás	0.006539	0.043206	0.038282	0.023902	0.003613	0.116037	0.02024
Maranhão	0.005243	0.015167	0.012186	0.000896	0.003974	0.003941	0.000716
Espírito Santo	0.004654	0.003671	0.013574	0.000299	0.043232	0.002408	0.022748
Rondônia	0.004419	0.013299	0.004518	0.00239	0.00566	0.000766	0.000896
Distrito Federal	0.003653	0.009702	0.011635	0.115327	0.291426	0.053093	0.001791
Mato Grosso	0.003358	0.019967	0.012929	0.001793	0.007105	0.001204	0.002328
Roraima	0.002003	0.008598	0.003853	0.000299	0.002288	0.000219	0.001433
Acre	0.000471	0.004345	0.002334	0	0.000963	0.000219	0
Piauí	0.000295	0.007432	0.00764	0	0.000723	0.000109	0.001075
Amapá	5.89E-05	0.00661	0.002486	0	0.003613	0.000109	0

After gj is considered in a normalized decision matrix, the mean (Equation 3) and the standard deviation (Equation 4) are then calculated. The Gaussian factor (or coefficient of variation) is used to weigh the criteria (Equation 5). The Gaussian factor is then multiplied by the normalized matrix, which is the aggregation operation (Equation 6).

$$\mu = \frac{\sum_i g(a_i)}{n_i} \tag{3}$$

$$\sigma = \sqrt{\frac{\sum (g(a_i) - \mu)^2}{n-1}} \tag{4}$$

$$c_v = \frac{\sigma}{\mu} \tag{5}$$

$$\sum_j^{i=1} g_{ij} w_j \tag{6}$$

Table 5 displays the values obtained for the mean, standard deviation, Gaussian factor, and normalized Gaussian factor.

Table 5. Mean, Standard Deviation, Gaussian Factor, and Gaussian Normalized Factor.

Criterion	Average	Standard deviation	Gaussian Factor	G. Norm Factor
Work-related mental disorders	0.037037	0.060699	1.638873	0.120406
Work accidents	0.037037	0.072612	1.960523	0.144037
Occupational accidents with exposure to biological material	0.037037	0.058014	1.566373	0.115079
Cancer as a function of work	0.037037	0.081576	2.202552	0.161818
Work-related dermatosis	0.037037	0.065837	1.777601	0.130598
Work-related hearing loss	0.037037	0.067382	1.819301	0.133661
Work-related pneumoconiosis	0.037037	0.098001415	2.646038195	0.194400673

The final step is to multiply the Gaussian factor by the normalized decision matrix to determine the prioritization order of the states that require greater attention to worker health actions (Table 6).

The analysis of the results shown in Table 6 presents a complex and diverse overview of workers' health across the Brazilian states, focusing particularly on the marked differences among São Paulo, Minas Gerais, and Acre. This dissection not only enhances the understanding of specific occupational health intervention needs, but also serves as a foundation for the development of more targeted and effective public health strategies.

São Paulo has an impressive AHP-G value of 0.267803, and emerges as the epicenter of critical needs in worker health, a reality that reflects the unique challenges posed by its significant population density and vigorous economic activity. São Paulo's top-ranking position is distinct, compared with second-ranking Minas Gerais, which has an AHP-G value of 0.164025, and reveals a relatively lesser need for interventions. This differentiation between the two states underscores not only the heterogeneity of working conditions and occupational risks faced by workers, but also indicates variations in worker health priorities, which should be considered in public policy planning. (Karino et al., 2012).

At the opposite extreme, Acre has an AHP-G value of 0.001106, and was the state with the lowest immediate priority in this study. The pronounced contrast between the needs of São Paulo and those of Acre illustrates the substantial disparities that exist in terms of occupational health risks, and the need for worker health interventions, highlighting how important it is to have a regionalized approach for developing and implementing occupational health strategies. The striking difference in the AHP-G indices signals the importance of tailoring interventions to the specific reality of each state, and ensuring that public policies are both relevant and effective in promoting worker health.

Table 6. Normalization of results and order of prioritization of states.

State	Population	AHP-G	Rank
São Paulo	44,035,304	0.267803	1
Minas Gerais	20,593,356	0.164025	2
Paraná	11,597,484	0.108819	3
Distrito Federal	2,570,160	0.067342	4
Rio Grande do Sul	11,422,973	0.059549	5
Mato Grosso do Sul	2,619,657	0.052917	6
Bahia	15,127,000	0.036482	7
Rio de Janeiro	6,747,815	0.035806	8
Goiás	6,523,222	0.0352	9
Santa Catarina	7,252,502	0.023074	10
Rio Grande do Norte	3,408,510	0.022274	11
Ceará	8,778,576	0.02057	12
Pernambuco	9,277,727	0.018583	13
Tocantins	1,496,880	0.013615	14
Espírito Santo	3,885,049	0.01309	15
Alagoas	3,321,730	0.012882	16
Paraíba	3,914,421	0.007653	17
Mato Grosso	3,224,357	0.0066	18
Pará	8,073,924	0.006037	19
Maranhão	6,851,000	0.005548	20
Amazonas	3,873,743	0.005471	21
Sergipe	2,225,000	0.004572	22
Rondônia	1,748,531	0.00437	23
Roraima	488,072	0.002578	24
Piauí	3,194,718	0.002303	25
Amapá	751,000	0.001732	26
Acre	790,101	0.001106	27

This preliminary analysis of the results, focusing on the discrepancies between São Paulo and other states (Yokoyama et al., 2013), reinforces the need for a worker health policy based on a thorough understanding and clear distinction of the regional variations involved in occupational risks. The AHP-G method emerges as an indispensable tool in this context, by providing a solid quantitative foundation for the allocation of funds and the formulation of policies aimed at improving the health of Brazilian workers. The disparity in AHP-G values between the states underscores the importance of personalized, evidence-based approaches, emphasizing that uniform strategies may not be suitable to meet the diverse needs of the states. Thus, the development of public worker health policies demands strategic and adaptive planning, capable of responding efficiently and effectively to the specific demands of each region of the country.

3 Results and discussion

The results indicate that pneumoconiosis and work-related cancer received the highest scores, hence suggesting that these are the most critical criteria for prioritizing actions. However, this conclusion warrants a deeper analysis. Do these high values reflect a higher prevalence or greater impact of these conditions on worker health? On the other hand, work accidents involving exposure to biological material presented the lowest value, thus raising questions about the possible underestimation of the risks associated with these types of accidents.

Regarding the states, São Paulo showed the greatest need for actions to ensure worker health, followed by Minas Gerais and Paraná. The positive correlation of 0.9 between 'Population' and 'AHP-G' suggests a tendency that states with larger populations have higher AHP-G values. However, it is crucial to bear in mind that a larger population might lead to a greater visibility of problems, and may not necessarily indicate less effective occupational health management.

The implementation of the AHP-G method in this study provided a structured basis for decision-making, although it is important to emphasize that the results depended significantly on the quality and comprehensiveness of the data used. While the method facilitated the prioritization of risks and preventive actions, a more critical analysis of the data and its limitations was needed to ensure accurate interpretation. Furthermore, the insights derived from the application of the AHP-G are valuable for formulating public policies, but must be used cautiously, considering the variable contexts and complexities of the work environment. The identification of knowledge gaps points to the need for further research, especially in underrepresented or poorly understood areas. Finally, the use of the AHP-G provided detailed insights into the economic, social, and health impacts of work accidents and occupational diseases. This in-depth view is essential, but must be complemented with qualitative perspectives for a holistic understanding of workplace health issues to benefit workers, employers, and society.

4 Final thoughts

This study was conducted using the TABNET database from DATASUS. The AHP-G method offers a valuable contribution to the field of workers' health in Brazil. By prioritizing occupational health actions based on careful analysis, pneumoconiosis and occupational cancer could be identified as critical areas requiring effective, focused interventions. Notably, the state of São Paulo emerged as the most critical region, illustrating the urgent need for targeted public policies and occupational health strategies.

The stark differentiation between São Paulo and other states, such as Minas Gerais and Acre, highlights regional disparities in worker health needs. These differences underscore the importance of personalized approaches in public policy formulation, considering the demographic and economic particularities of each region. The positive correlation between the population of the states and the AHP-G indices reinforces the relationship between population size and occupational health requirements, emphasizing the need for funds and strategies adapted to the reality of each state.

This study transcends a quantitative analysis, by proposing a solid basis for informed decision-making in the field of workers' health. It also provides a refined analytical tool for policymakers and researchers, by showing the effectiveness of the AHP-G method in assessing the needs of states. However, it is crucial to recognize the limitations associated with the quality and scope of the available data, as well as the need to consider additional variables in future research to achieve a more comprehensive understanding of occupational health needs.

The implementation of the AHP-G method sheds light on the path toward more effective worker health management in Brazil, and indicates future directions for enhancing occupational health strategies in the Brazilian context. The insights derived from this analysis are indispensable for formulating more efficient public policies, although they must be applied discerningly, and take into account the variable complexity of the work environment.

Thus, while this study marks a significant advancement in prioritizing worker health actions, it also broadens the horizon for future investigations. Subsequent research to explore AHP-G applied to different contexts and involving additional variables is essential to further our understanding of worker health needs across various populations and environments. In so doing, the current study not only contributes to the existing literature but also establishes a foundation for future research initiatives and policy formulation in the field of occupational health.

An important limitation of this study lay in the exclusive use of the DATASUS-derived data available on TABNET. Although comprehensive, it may not capture all the nuances of worker health conditions in each state. The quality and completeness of the recorded data may range, and thus potentially influence the accuracy of the analyses and conclusions.

This limitation can be overcome by integrating data from multiple sources in future research work, including hospital records, union reports, and epidemiological studies. This would make it possible to gain a more holistic view of worker health conditions. Additionally, it would be valuable to investigate the impact of specific occupational health interventions implemented in response to the priorities identified, and assess their effectiveness in improving the health and safety conditions of workers. Other promising directions for future research include applying the AHP-G method in other regions and contexts, and adapting it to address different public health issues. This would definitively contribute to the development of more effective and evidence-based occupational health strategies.

Statement on Data Availability

The data used is available and can be provided upon request to the authors.

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Authors contribution

Ana Carolina Russo worked on the conceptualization and theoretical-methodological approach. The theoretical review was conducted by Ana Carolina Russo and Edison Russo. Data collection was coordinated by Ana Carolina Russo. Ana Carolina Russo and Edison Russo participated in data analysis. All authors were involved in writing and the final review of the manuscript.