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Scientometric Analysis of Research Work on Mental Workload

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Abstract

Background: Modern work environments characterized by high cognitive demand can generate significant mental workload. Studying this phenomenon helps us to understand how cognitive demands affect workers' performance, health, and well-being. A scientometric analysis of mental workload allows for the identification of trends, gaps, and emerging areas in scientific research. Objective: This study aims to analyze the development of the literature on mental workload in terms of the most relevant studies, main authors and their networks, main journals and keywords, countries and institutions leading research, and main research areas. Methods: A scientometric and bibliometric analysis was conducted through a search of scientific articles published in the Web of Science (WoS) database between 1975 and 2024. Results: Of the total number of publications, 71.2% occurred in the last 10 years. A total of 87.16% of the articles have 0 citations or less than 50. The countries with the greatest production and influence are the United States, China, and Germany. Among the main areas of study were "Engineering", "Psychology", "Transportation", and "Surgery." Conclusions: Publications and citations on the subject have grown significantly. This justifies the need to study mental workload in other areas and cultural contexts.

Keywords: mental workload; scientometrics; Web of Science

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1. Introduction

Nowadays, work environments, among other factors, are becoming increasingly complex due to the growing incorporation of technologies, making certain processes easier. However, it entails greater demands with a potential overload for workers (Young et al., 2015). According to the literature, the physical and social aspects of the work environment, such as job-specific characteristics and future expectations, significantly influence employees' well-being. Workplace conditions and interpersonal relationships can impact staff well-being, which in turn has broad effects on productivity (Dumitriu et al., 2025). Among them, mental workload (MWL) is found to be one of the most important factors (Rubio-Valdehita et al., 2017).

Notwithstanding the development of research on MWL, there is no universally accepted definition due to the abundance of theoretical work related to the construct, phenomena interpretations, and contributions from different fields (Longo et al., 2022). Broadly speaking, MWL can be intuitively defined as "the total cognitive work required for a human being to perform a task over time" (Longo et al., 2022, p. 8) or as "the level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support, and past experience" (Young & Stanton, 2005, chap. 39-1). MWL is a multidimensional construct. Therefore, due to the

Interaction among tasks, persons and situations, it is affected by different factors whose number and type are still unclear (O'Donnell & Eggemeier, 1986; Longo et al., 2022).

Different models have been proposed to explain the impact of MWL. On the one hand, according to the resource or attentional model, the demand for resources increases as the difficulty of the task increases. If resources are not sufficient, performance is compromised (Wickens, 2002, 2008). This results in higher error frequency and poorer individual performance, especially when time pressure merges with capacity issues (Liu & Lo, 2018). On the other hand, integrative resource models account for the multidimensional nature of MWL (Hart & Staveland, 1988). Thus, MWL includes subjective processes that would affect physical abilities, leading to fatigue, errors, changes in behavior and work performance (Rubio et al., 2010; Tao et al., 2019).

Negative effects occur in all situations where MWL levels are inadequate (Wickens et al., 1998; González et al., 2005). An imbalance between task demands and workers' capabilities can occur due to mental work overload or underload. In the case of overload, workers are subject to more demands than they can cope with. Meanwhile, with underload, workers are subject to very simple tasks with little cognitive demand (Cabrera et al., 2010). The risks of overload have been identified early on; however, other current concerns are stress, boredom, and underload (Hancock & Warm, 1989; Becker et al., 1991), affecting workers' performance and satisfaction.

Empirical evidence on MWL covers a wide range of tasks, and different methods have been used for its measurement (Longo et al., 2022). Tasks requiring repetitive activities or great focus, such as those performed by train drivers, vehicle drivers, or flight operators, have been frequently investigated. Hassanzadeh-Rangi et al. (2023) conducted a study on train drivers and showed that the MWL measured through NASA-Task Load Index (TLX) (Hart & Staveland, 1988) had a significant correlation with work fatigue. Furthermore, MLW increased significantly at the end of the workday, with this being the moment with the highest probability of accidents. In simulated flight multitasking, heart rate and prefrontal cortex (PFC) activation were shown to be useful for identifying changes in MWL using a combination of functional near-infrared spectroscopy (fNIRS) and electrocardiogram (ECG) (Li et al., 2022).

MWL in healthcare workers is of special interest, because healthcare is considered one of the most unsafe work environments (Moore & Kaczmarek, 1990) due to exposure to biological, chemical, physical, ergonomic, and psychosocial hazards (Mossburg et al., 2019). The study by (Espinoza-Aguilera & Luengo-Martínez, 2022) shows that during the COVID-19 pandemic, 78.3% of Chilean healthcare workers showed a high MWL measured with the Subjective Mental Workload Scale (ESCAM, for its Spanish acronym) (Rolo et al., 2009). Another study found a moderate negative correlation between MWL of Chinese nurses and public health emergency response capability (He et al., 2024). In a systematic review conducted with nurses from the emergency units of developing countries, they were found to experience increased MWL that hindered quality of care improvements (Yuan et al., 2023). Moreover, surgeons in Iranian hospitals with a high MWL were shown to have negative effects on their performance (Jalali et al., 2023)

Therefore, assessing MWL is key in the study of workers' welfare, performance optimization, and error minimization (Longo et al., 2022). Although MWL has been studied in terms of different tasks, techniques, and measurement instruments, there are no published studies on the evolution of scientific production on this matter. In this sense, this study lays the groundwork for the literature published between 1975 and 2024 on MWL, in addition to being a literature review guide for future research works. Consequently, the objective of this study is to analyze the development of literature on mental workload in terms of the most relevant studies, main authors and their networks, main journals and keywords, countries and institutions leading research, and main research areas. To achieve the objective, a scientometric analysis of the literature on mental workload was conducted by searching for scientific articles published in the Web of Science (WoS) database for the specified period. Additionally, scientometric analyses were applied to examine co-authorships and keyword co-occurrence.

As the first study of its kind on mental workload, the findings aim to serve as a guide for future lines of research, providing direction to researchers regarding the development of studies on this construct.

The following section presents a description of the materials and methods used. It continues with the findings resulting from the analysis. Finally, the results are discussed, concluding with the insights drawn from them.

2. Materials and Methods

This is a descriptive conclusive research work with a longitudinal cut (Malhotra, 2004), with a non-experimental design of bibliographic research (Campo-Ternera et al., 2018). It was developed based on a scientometric and bibliometric analysis.

Scientometrics is the study of the quantitative aspects of scientific and technological literature, and it is used to develop science policies in countries and organizations (Van Raan, 1997; Garfield, 2009). Bibliometrics, in turn, is the method used to quantitatively analyze the production of scientific literature (De Solla Price, 1963; White & McCain, 1989; Bailón-Moreno et al., 2005). Through these approaches, patterns, relationships, trends, and indicators are identified based on scientific information published in news articles or scholarly journals (Michán & Muñoz-Velasco, 2013).

Considering the large number of articles that can be found in a given area, the evolution of the subject of study can be investigated by means of bibliometric techniques, thus contributing to improve its understanding (Expósito-López & Olmedo-Moreno, 2020). This is relevant considering that the process of scientific research has accelerated with the emergence of electronic journals. The publication dynamics is more efficient, open, and massive, with new access technologies and organizational models to exploit digital collections in an innovative way (Michán & Muñoz-Velasco, 2013).

The questions this study seeks to answer are outlined below:

- What is the time evolution of the MWL study?
- What are the most relevant studies on MWL?
- What are the main authors and their networks researching MWL?
- What are the main journals and keywords on MWL?
- Which countries and institutions are leading research on MWL?
- What are the main areas of MWL research?

The bibliometric indicators used for the analysis were articles, citations, journals, institutions, authors, and countries. Furthermore, scientometric analyses were conducted for the review of co-authorships between authors, institutions, countries, and the co-occurrence of keywords related to MWL, which allowed designing a detailed map with key concepts based on frequency data and their respective clusters. The indicators used, such as the number of publications, aim not only to measure productivity but also influence, through metrics like the "h-index" or Hirsch index, and the "impact factor". The former is a measure that seeks to reflect the balance between the number of scientific publications by a person and the impact they have, as measured by the number of citations received. Hirsch (2005) defined h-index as "A scientist has index h if h of his or her Np articles have at least h citations each and the other (Np-h) articles have fewer than h citations each". The latter refers to the average number of citations received by articles published in a journal over the previous two and five years. The "journal quartile (Q)" was also included, which is mainly used to assess the quality of scientific journals within their subject area. In addition, collaboration indicators such as co-authorship networks were used, as they reveal collaborative work dynamics and may be associated with greater impact. These indicators aim to provide a broad and in-depth view of the development of the literature on mental workload.

Data were studied using social network analysis based on graph theory in VOSviewer software version 1.6.19 (van Eck & Waltman, 2010). Among the advantages of using VOSviewer are its accessibility, ease of use, and its potential to identify emerging areas and collaboration networks. Moreover, several articles indexed in Web of Science have employed this tool (Araya-Castillo et al., 2021; Hernández-Perlines et al., 2023; Rubiales-Núñez et al., 2024).

Thus, in March 2025, a search was conducted for scientific articles published in the Web of Science (WoS) database and its indicators Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index, Arts and Humanities Citation Index, and Emerging Sources Citation Index. The following search strategy was used: (TS = ("mental workload")) AND DT = (article) Timespan: 1975–2024. For the analysis, all articles found by this strategy were included.

The Web of Science (WoS) database was selected due to its strong reputation, ease of access, and broad coverage of relevant scientific literature, as the analysis focused exclusively on peer-reviewed and high-impact studies (Granda-Orive et al., 2013; Velt et al., 2020). On the other hand, WoS records begin in 1975, which is why the analysis starts from that year. The endpoint is set in 2024 to ensure the inclusion of data from the complete year.

Table 1 shows the phases of the scientometric analysis, while Table 2 shows the criteria used for the association analyses in VOSviewer.

Table 1. Main phases of the scientometric analysis.

Description	Phase
Phase 1: Recovery	In this phase, the sources of digital bibliographic information (database) to be used are selected. The search must consider the appropriate terms, operators, and criteria, and it involves selecting the literature that will constitute the study set.
Phase 2: Migration	It comprises the extraction of meta-data from the selected records, transfer of the extracted information, and load of this information into a new database. At this stage, the records must be curated to ensure that they are standardized and refined.
Phase 3: Analysis	It comprises the quantitative processing of the literature. This stage involves procedures such as bibliometric indicator collection and use of statistical methods.
Phase 4: Visualization	Figures, graphs, diagrams, and maps are created to reflect the trends and results of the analyses briefly and attractively. Visualization generally focuses on what is considered to have the greatest contribution or what is considered to lead to a better understanding of the subject.
Phase 4: Interpretation	In this phase, results are contextualized and interpreted to establish research trends and methodological and/or social interactions with respect to a research group, institution, region, country, topic, discipline, or field of knowledge or study model, among others.

Prepared by the authors based on Michán and Muñoz-Velasco (2013).

Table 2. Criteria for analysis in VOSviewer.

Type of Analysis	Criteria
Co-authorship	Minimum of five articles per author and minimum of zero citations per author
Co-authorship and organizations	Minimum of 10 documents per organization and minimum of 0 citations per organization
Citation and organizations	Minimum of 10 documents per organization and minimum of 0 citations per organization
Co-occurrence of words	Minimum of 15 co-occurrences

Source: Prepared by the authors.

3. Results

3.1. Articles and Citations in the Area of Study

We found 2803 scientific publications on MWL in the WoS database. The search was conducted considering the 1975–2024 period. The first two articles indexed in this database were published in 1977 by Alan Traviss Welford and Winfried Hacker, and it was entitled "Mental workload as a function of demand, capacity, strategy and skill" and "Internal representation of task structure and mental load of work: approaches and methods of assessment", both published in the Travail Humain Journal belonging to quartile 4.

Figure 1 shows that 71.2% of the total number of publications in the study period occurred in the last 10 years, while 48.7% occurred in the last 5 years. This shows that the increase in publications has increased in recent years. Moreover, the coefficient of determination (R^2 = 0.9856) indicates a good fit of the model; thus, we can state that there has been an increase in literature on MWL. The sustained increase in publications observed between 2000 and 2010 may be related to a growing concern for workplace environments, which likely encouraged scientific production on the topic.

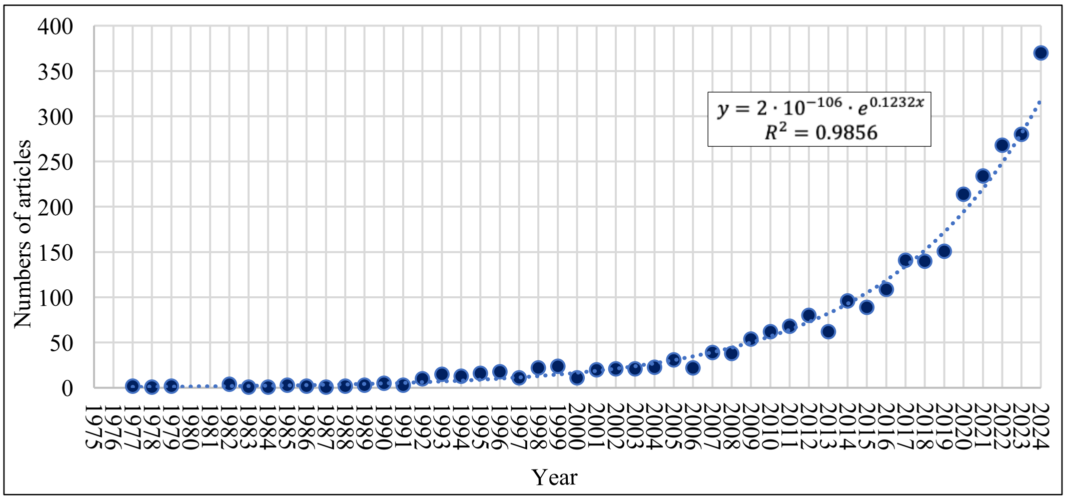

Figure 1. Growth in scientific production.

From the published articles, a total of 70,652 citations were obtained for the study period. Figure 2 shows that almost 60% of the total number of citations for the study period was made in the last 5 years, with 2024 being the year with the highest number of citations (11,941). The coefficient of determination (R^2 = 0.8585) reflects a strong model fit. Similarly to what has been observed in scientific production, there has been a significant increase in the number of citations related to MWL.

Table 3 presents the number of articles by number of citations. Notably, 306 articles, equivalent to 10.92%, have not been cited. Moreover, 2137 articles (76.24%) have 1–50 citations and almost 5% have 100–600 citations.

Table 3. General citation structure.

Citations	Articles	Articles %
201–600 citations	39	1.39
101–200 citations	100	3.57
51–100 citations	221	7.88
1–50 citations	2137	76.24
0 citations	306	10.92
Total	2803	100.00

Prepared by the authors, based on data from Web of Science (2025).

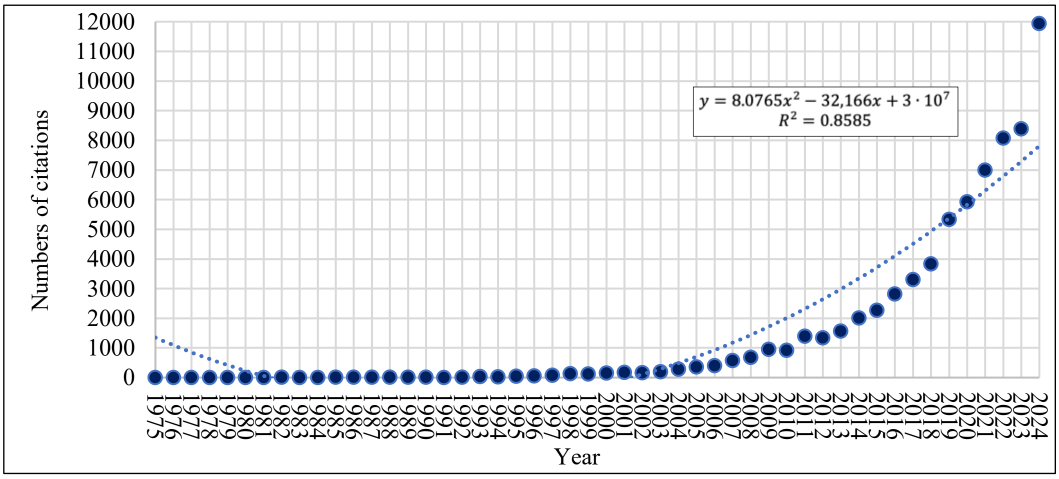

Figure 2. Total number of citations per year.

Of the 2803 articles, 115 articles exceed 115 citations and were the ones with the highest impact. Chris Berka's article in 2007 and Ray Fuller's article in 2005 account for 2.48% (n = 572) and 2.34% (n = 540) of the total citations (n = 23,049) for the group of publications indicated. Berka et al. (2007) article, published in the journal Aviation Space and Environmental Medicine (Q4), studied the feasibility of monitoring electroencephalographic (EEG) indices of engagement and workload quantified during cognitive testing and found that these correlated with subjective and objective performance metrics. Fuller (2005) published an article in the journal Accident Analysis and Prevention (Q1) and discussed the implications of the task capability interface model, which describes the dynamic interaction between the determinants of task demand and driver capability. The article concludes that the difficulty of driving is inversely related to the difference between the driver's ability and demand of the driving task (Table 4). Thirdly, the article by Hjortskov et al. explores how mental stress affects physiological parameters during computer-based work. The studies by Wickens (2008), Rubio et al. (2004), and Gevins et al. (1998) focus on models and methods for measuring mental workload, while Ayaz et al. (2012), Recarte and Nunes (2003), and Leeb et al. (2007) examine mental workload assessment in various contexts. These articles represent some of the most influential contributions in the field, covering areas such as applied neuroscience, traffic psychology, and computational ergonomics.

Table 4. Most cited articles.

R	Title	Author(s)	Year	Journal	TC
1	EEG correlates of task engagement and MWL in vigilance, learning, and memory tasks	Berka, Chris; Levendowski, Daniel J.; Lumicao, Michelle N.; Yau, Alan; Davis, Gene; Zivkovic, Vladimir T.; Olmstead, Richard E.; Tremoulet, Patrice D.; Craven, Patrick L	2007	Aviation Space and Environmental Medicine	572
2	Towards a general theory of driver behaviour	Fuller, R	2005	Accident Analysis and Prevention	540
3	The effect of mental stress on heart rate variability and blood pressure during computer work	Hjortskov, N; Rissen, D; Blangsted, AK; Fallentin, N; Lundberg, U; Sogaard, K	2004	European Journal of Applied Physiology	529
4	Multiple resources and mental workload	Wickens, Christopher D	2008	Human Factors	501
5	Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods	Rubio, S; Diaz, E; Martin, J; Puente, JM	2004	Applied Psychology-an International Review-Psychologie Appliquee-Revue Internationale	496

Table 4. *Cont.*

R	Title	Author(s)	Year	Journal	TC
6	Optical brain monitoring for operator training and mental workload assessment	Ayaz, Hasan; Shewokis, Patricia A.; Bunce, Scott; Izzetoglu, Kurtulus; Willems, Ben; Onaral, Banu	2012	Neuroimage	423
7	Mental workload while driving: Effects on visual search, discrimination, and decision making	Recarte, MA; Nunes, LM	2003	Journal of Experimental Psychology-Applied	412
8	Monitoring working memory load during computer-based tasks with EEG pattern recognition methods	Gevins, A; Smith, ME; Leong, H; McEvoy, L; Whitfield, S; Du, R; Rush, G	1998	Human Factors	362
9	Brain–computer communication: Motivation, aim, and impact of exploring a virtual apartment	Leeb, Robert; Lee, Felix; Keinrath, Claudia; Scherer, Reinhold; Bischof, Horst; Pfurtscheller, Gert	2007	IEEE Transactions on Neural Systems and Rehabilitation Engineering	346
10	Short assessment of the Big Five: robust across survey methods except telephone interviewing	Lang, Frieder R.; John, Dennis; Luedtke, Oliver; Schupp, Jurgen; Wagner, Gert G	2011	Behavior Research Methods	321

Prepared by the authors, based on data from Web of Science (2025). Title: Article title; Author: Article author; Year: Year of publication; TC: Total citations of article.

Table 5 shows that for the total of 2803 publications on MWL, a total of 8892 authors are identified, either as main author or co-author. The 10 most cited authors account for 12.97% (n = 9163) of the total number of citations, with Parasuraman, R. of George Mason University being the most cited author with 17 publications on the subject, appearing in 5 of them as first author, and accounting for almost 3% of the citations. This author ranks seventh among the 10 most productive authors, and 3 of his articles are among the 50 most cited. The second most influential author is Wilson, GF. of Trinity College, Dublin, with 12 publications and almost 2% of the citations (n = 1216).

Table 5. Most influential authors.

R	Author's Name	Institution	TP-SV	TC-SV	% of 70,652	h-Index SV	TP-A	TC-A
1	Parasuraman, Raja	George Mason University	17	1775	2.51	16	231	17,593
2	Wilson, GF	Trinity College Dublin	12	1216	1.72	11	152	4172
3	Matthews, Gerald	University of Central Florida	17	873	1.24	12	191	9757
4	Borghini, Gianluca	Sapienza University of Rome	20	841	1.19	12	106	3627
5	Babiloni, Fabio	Sapienza University Rome	19	811	1.15	11	441	13,889
6	De Waard, Dick	University of Groningen	16	783	1.11	13	113	3407
7	Ayaz, Hasan	Drexel University	9	772	1.09	7	188	4700
8	Di Stasi, Leandro Luigi	University of Granada	15	705	1.00	13	62	2049
9	Di Flumeri, Gianluca	Sapienza University of Rome	19	699	0.99	11	94	2158
10	Arico, Pietro	Sapienza Univ Rome	15	688	0.97	11	117	2921
Total			159	9163	12.97	12	1695	64,273

Prepared by the authors, based on data from Web of Science (2025). R: Ranking; TP-SV: Total articles for the search vector; TC-SV: Total citations for the search vector; %: Percentage of citations over total citations (70,652); h-index SV: Hirsch index for the author in the search vector; TP-A: Total articles by author; TC-A: Total citations for the author.

3.2. Main Authors

The author is validated by the number of articles (extent) and the number of times the author is cited (depth). In this study, 10 authors with 16 or more publications on MWL were identified (Table 6). Of these, 6 are among the top 10 most influential ones. Gianluca Borghini of Sapienza Università di Roma stands out with the highest number of articles and the fourth most cited position. Furthermore, it is observed that the 10 authors, together, have 6.31% of the total number of publications on MWL, and none of the authors exceeds 1% of the total number of publications.

Table 6. Most productive authors.

R	Author's Name	Institution	TP-SV	TC-SV	AC-SV	% of 2803	h-Index SV	h-Index	TP-A	TC-A
1	Borghini, Gianluca	Sapienza Università di Roma	20	841	42.05	0.71	12	33	106	3627
2	Zhang, Jianhua	Beijing University of Technology	20	606	30.3	0.71	14	22	150	1790
3	Babiloni, Fabio	Sapienza University Rome	19	811	42.68	0.68	11	66	441	13,889
4	Di Flumeri, Gianluca	Sapienza University of Rome	19	699	36.79	0.68	11	26	94	2158
5	Hwang, Sheue-Ling	National Tsing Hua University	17	301	17.71	0.61	9	17	112	971
6	Matthews, Gerald	University of Central Florida	17	873	51.35	0.61	12	54	191	9757
7	Parasuraman, Raja	George Mason University	17	1775	104.41	0.61	16	67	231	17,593
8	Causse, Mickael	Universite de Toulouse	16	606	37.88	0.57	11	24	63	1214
9	De Waard, Dick	University of Groningen	16	783	8.94	0.57	13	35	113	3407
10	Hancock, Peter A	University of Central Florida	16	602	37.63	0.57	11	62	385	13,236
Total			177	7897	40.97	6.31	12	40.6	1886	67,642

Prepared by the authors, based on data from Web of Science (2025). R: Ranking; TP-SV: Total articles for the search vector; TC-SV: Total citations for the search vector; AC-SV: Average citations in the search vector; %: Percentage of articles over the total; h-index SV: Hirsch index for the author in the search vector; TP-A: Total articles by author; TC-A: Total citations for the author.

Figure 3 and Table 7 show the co-authorship between authors for the study concept. There are two clusters that show a group of authors who have worked together for publications. Cluster 1 (red) contains three of the most productive and influential authors: Babiloni, Borghini, and Di Flumeri. In cluster 2 (green), none of the authors are in the aforementioned ranking. Regarding the nodes, in the red cluster Babiloni and in the green cluster Bezerianos are the ones with the highest production in the network. Concerning the links, the thickest connection appears among Babiloni, Arico, Di Flumeri, Borghini, and Sciaraffa, indicating a strong collaborative intensity within this group.

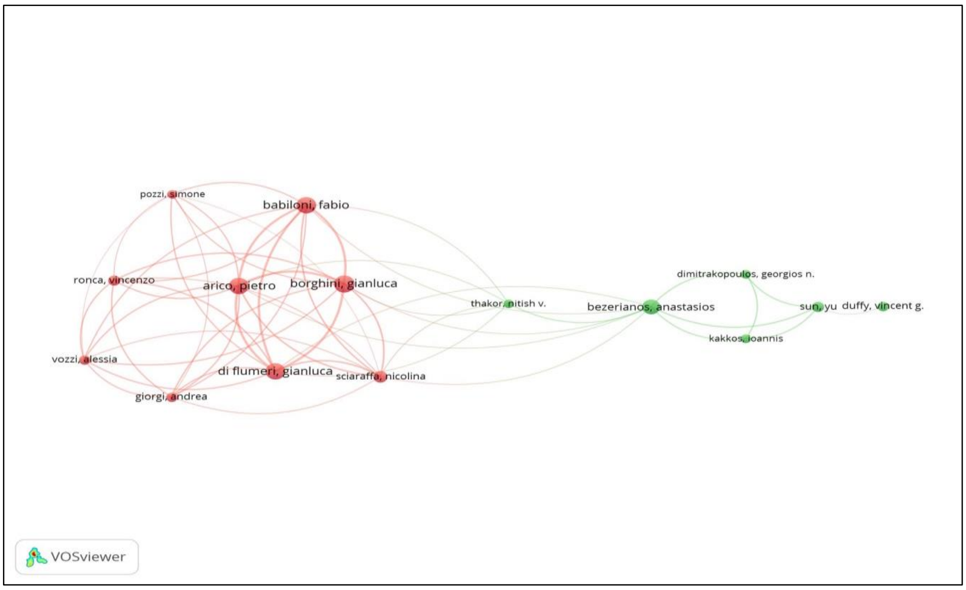

Figure 3. Co-authorship network for scientific production.

Table 7. Co-authorship clusters for scientific production.

Cluster 1 (Red-9)	Cluster 2 (Green-6)
arico, pietro	bezerianos, anastasios
babiloni, fabio	dimitrakopoulos, georgia
borghini, gianluca	duffy, vincent g.
di flumeri, gianluca	kakkos, ioannis
giorgi, andrea	sun, yu
pozzi, simone	thakor, nitish v.
ronca, vincenzo	
sciaraffa, nicolina	
vozzi, alessia	

3.3. Main Journals

Out of a total of 851 journals, 49 have published 10 or more articles on the subject analyzed. Table 8 presents the 10 scientific journals with the highest number of articles published on the topic under study, which jointly account for slightly more than a quarter of the total number of publications. The journals Human Factors (quartile 2) and Ergonomics (quartile 3) jointly account for almost 10% of the publications. In the case of Human Factors, it also has the highest number of citations and h-index. Both journals aim to publish evidence on studies related to physical, cognitive, organizational, and environmental ergonomics, thus contributing to enhance the understanding of human interactions with products, equipment, environments, and systems from a theoretical, practical, or applied approach.

Table 8. Web of Science scientific journals in which the production is published.

R	Journal	NP	% of 2803	TC-SV	AC-SV	h-Index	IF 2023	IF 5Y	Q
1	Human Factors	136	4.85	7037	51.74	43	2.9	3.8	2
2	Ergonomics	119	4.25	4094	34.4	37	2	2.8	3
3	Applied Ergonomics	90	3.21	2279	25.32	30	3.1	3.7	1
4	International Journal of Industrial Ergonomics	77	2.75	1977	25.68	25	2.5	2.9	2
5	Transportation Research Part F: Traffic Psychology and Behaviour	72	2.57	2243	31.15	25	3.5	4.1	1
6	Accident Analysis and Prevention	60	2.14	3657	60.95	31	5.7	5.9	1
7	Frontiers in Human Neuroscience	51	1.82	1474	35.8	24	2.4	3	3
8	Sensors	37	1.32	733	14.66	15	3.4	3.7	2
9	International Journal of Human Computer Interaction	43	1.53	412	9.58	11	3.4	4.5	1
10	Work: A Journal of Prevention, Assessment & Rehabilitation	41	1.46	250	61	9	1.7	1.9	3
Total		726	25.90	24,156	35.03	25			

Prepared by the authors, based on data from Web of Science (2025). Ranking; NP: Total number of articles with the search vector; % of 2803: Percentage of total articles in the search vector; AC-SV: Average number of citations per article in the search vector; IF Y5: Impact factor of the journal in the last five years; Q: quartile in the category.

Furthermore, the journal Accident Analysis and Prevention (quartile 1), which is sixth in this ranking, is the journal with the highest average for this indicator. Furthermore, it is found that 4 of the 10 journals are in quartile 1.

Regarding the research areas of the journals, Human Factors, Ergonomics, Applied Ergonomics, International Journal of Industrial Ergonomics, and Work: A Journal of Prevention, Assessment & Rehabilitation share a common focus on ergonomics and occupational health, approached from various disciplines and perspectives. Accident Analysis and Prevention and Work: A Journal of Prevention, Assessment & Rehabilitation emphasize safety and accident prevention. Finally, Frontiers in Human Neuroscience and Transportation Research Part F: Traffic Psychology and Behaviour concentrate on neuroscience and cognitive psychology.

3.4. Main Institutions

Table 9 shows the ranking of the 10 institutions with the highest number of publications for MWL, which together account for 15.34% of the total number of publications. The United States Department of Defense is the institution with the most publications, highest number of citations, and highest h-index, while the University System of Ohio has the highest average number of citations (54.72). Although they are not included in this ranking, George Mason University, University of Illinois System, University of Groningen, and Universidad de Granada have more than 1000 citations. This is graphically illustrated in Figure 4, with larger nodes representing these countries, China being the second largest node. However, in Table 9, China is represented by only 1 of the 10 institutions (Beihang University).

Table 9. Institutions associated with scientific production.

R	Institution	Country	TP-SV	% of 2803	h-Index	TC-SV	AC-SV
1	United States Department of Defense	United States	58	2.07	25	2412	41.59
2	Centre National de la Recherche Scientifique CNRS	France	48	1.71	22	1467	30.56
3	Universite de Toulouse	France	47	1.68	22	1832	38.98
4	State University System of Florida	United States	44	1.57	17	1230	27.95
5	Beihang University	China	43	1.53	14	576	13.4
6	United States Air Force	United States	39	1.39	20	1768	45.33
7	University System of Ohio	United States	39	1.39	22	2134	54.72
8	Texas AM University System	United States	38	1.36	14	564	14.84
9	Delft University of Technology	Netherlands	37	1.32	22	1544	41.73
10	Purdue University	United States	37	1.32	14	672	18.16
Total			430	15.34	19	14,199	32.73

Prepared by the authors, based on data from Web of Science (2025). Ranking; TP-SV: Number of publications in the search vector; % of 2442: Percentage of articles; h-index: Hirsch index in the search vector; TC-SV: Total articles for the search vector; AC-SV: Average number of citations in the search vector.

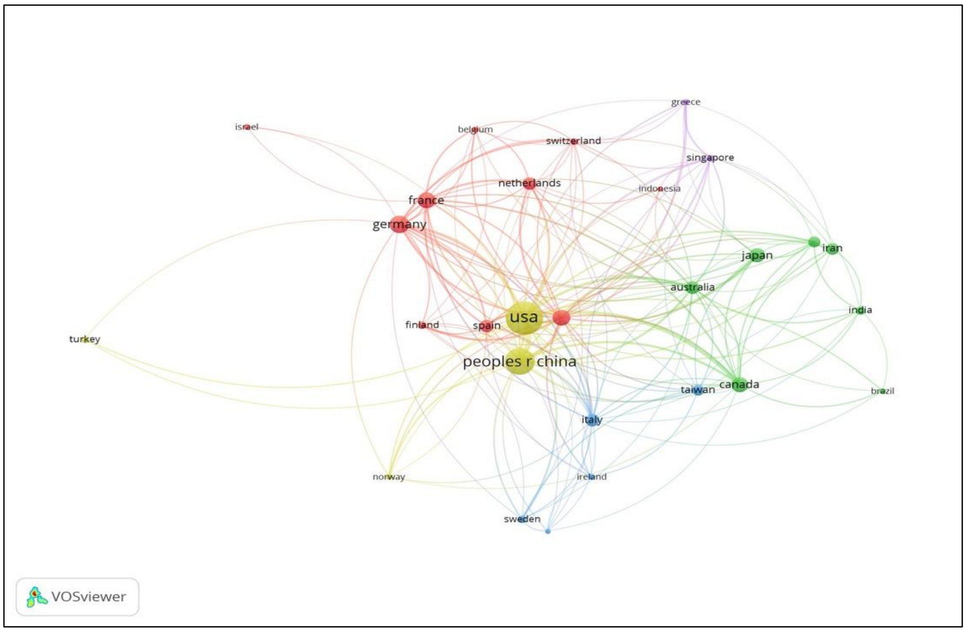

Figure 4. Countries with the highest number of co-authorships.

The scientometric analysis in Table 10 shows the most productive institution on MWL. Although 83 institutions out of 2705 have a minimum of 10 publications, only 67 have achieved it, making up a total of 11 clusters. The institutions with the highest amount of co-authorship in each cluster are shown in between parentheses, showing similar frequencies for this indicator with a minimum of 7 for Aalto University in cluster 11 (pale red) and a maximum of 26 for Sapienza Università di Roma in cluster 8 (brown). Additionally, the findings in Table 10 help identify active scientific communities and their areas of specialization. Cluster 1 (red) stands out with the highest number of institutions (12), including renowned universities such as Harvard Medical School, Johns Hopkins, University of Toronto, and University of British Columbia. This reflects a strong collaborative network among institutions from the United States, Canada, and Europe, with high scientific output. Clusters 2 (green) and 3 (light blue) each include 9 institutions. Cluster 2 brings together universities like MIT, Texas A&M, University of Michigan, and Delft University of Technology, which have a strong profile in engineering, technology, and applied ergonomics. Cluster 3 includes institutions such as Imperial College London, Penn State, Shanghai Jiao Tong University, and Université Laval, representing collaboration between Europe, Asia, and North America, with a focus on aeronautics, neuroscience, and industrial ergonomics.

Clusters 4 (yellow) and 5 (purple) include 8 and 7 institutions, respectively, mainly focused on technology and engineering. Finally, clusters 6, 7, 8, and 9 include between 6 and 2 institutions.

Table 10. Co-authorship clusters: organizations for scientific production.

Cluster 1 (Red-12)	**Cluster 2 (Green-9)**	**Cluster 3 (Light Blue-9)**	**Cluster 4 (Yellow-8)**	**Cluster 5 (Purple-7)**	
drexel univ (13)	clemson univ	cnrs	beihang university (10)	chinese acad sci	
harvard med sch	delft univ technol	imperial coll london	beijing jiaotong univ	harbin engn univ	
johns hopkins univ	mit	nanjing univ aeronaut & astronaut	city univ hong kong	hong kong polytech uni (9)	
mayo clin	texas a&m univ	penn state univ purdue univ	nanyang technol univ	south china univ technc	
simon fraser univ	univ cent florida (17)	purdue university	rmit univ	tianjin univ	
univ alberta	univ groningen	shanghai jiao tong univ	shenzhen univ	univ queensland	
univ british columbia	univ michigan	univ laval	tech univ munich	univ western australia	
univ maryland	univ wisconsin	univ toulouse (11)	tsinghua univ		
univ padua	virginia tech	univ waterloo			
penn univ					
univ toronto					
univ utah					
Cluster 6 (Calypso-6)	**Cluster 7 (Orange-5)**	**Cluster 8 (Brown-3)**	**Cluster 9 (Pink-3)**	**Cluster 10 (Pale Red-3)**	**Cluster 11 (Pale Red-2)**
huazhong univ sci & te (24)	air force res lab	brainsigns srl (25)	monash univ	arizona state univ	aalto univ (7)
natl univ singapore	george mason univ (15)	hangzhou dianzi univ	southeast univ (9)	technol univ dublin	coventry univ
northeastern univ	old dominion univ	sapienza univ rome (26)	univ southampton	univ granada (12)	
tongji univ	univ cincinnati				
univ illinois zhejiang univ	usaf				
zhejiang univ					

3.5. Main Countries

Table 11 shows the countries of origin of the publications, with the United States being the most productive one regarding MWL scientific articles, accounting for just over a quarter of the total number of publications (n = 756). Furthermore, it is the most influential country with the highest h-index, with a total of 25,316 citations and the second highest average number of citations, following the Netherlands, which ranks eighth in productivity. The second and third places are held by China and Germany, respectively, jointly accounting for 24.4% of the total number of publications. China has a high level of scientific output but a lower average number of citations compared to most countries listed in the table.

Table 11. Countries/regions associated with scientific production by author affiliation.

R	Countries/Regions	NP	% of 2803	TC-SV	AC-SV	h-SV
1	United States (USA)	756	26.97	25,316	33.49	81
2	People's Republic of China	471	16.80	7622	16.18	44
3	Germany	213	7.60	5518	25.91	39
4	England	180	6.42	6028	33.49	44
5	Canada	167	5.96	3994	23.92	33
6	France	162	5.78	4603	28.41	35
7	Japan	135	4.82	2220	16.44	25
8	Netherlands	122	4.35	5170	42.38	39
9	Spain	115	4.10	2854	24.82	26
10	Australia	113	4.03	2462	21.79	30
Total		2803	86.84	65,787	26.68	39.6

Prepared by the authors, based on data from Web of Science (2025). Ranking; NP: Total number of articles with the search vector; % of 2803: Percentage of total articles in the search vector; TC-SV: Total citations for the search vector; AC-SV: Average number of citations per article in the search vector; h-SV: Hirsch index for the author in the search vector.

Figure 4 shows co-authorships by country, where 28 of the 80 countries have published at least 20 co-authored articles. This information is grouped into five clusters (Table 12). In cluster 4 (yellow) the United States stands out with the highest number of co-authorships (221), followed by Germany, located in cluster 1 (in light blue) with 90 co-authorships. These results are consistent with those presented above regarding the leadership of the United States in terms of scientific production on MWL registered in the WoS database. The network reveals that countries with higher levels of scientific output (Table 11) also exhibit strong co-authorship ties.

Table 12. Co-authorship clusters by country/region.

Cluster 1 (Red-10)	Cluster 2 (Green-7)	Cluster 3 (Light Blue-5)	Cluster 4 (Yellow-4)	Cluster 5 (Purple-2)
Belgium	Australia	Denmark	Norway	Greece
England	Brazil	Ireland	People's Republic of China	Singapore (47)
Finland	Canada (91)	Italy (58)	Turkey	
France	India	Sweden	USA (221)	
Germany (90)	Iran	Taiwan		
Indonesia	Japan			
Israel	South Korea			
Netherlands				
Spain				
Switzerland				

3.6. Research Areas

Table 13 shows the research areas in which the articles published in the WoS database were classified. Notably, this registration is not exclusive; hence, an item may be classified in more than one category. Among the 2803 articles published on "Mental Workload", the dominant research area was Engineering, accounting for 44.77% (1255 articles), likely due to its focus on system design, ergonomics, automation, and the evaluation of complex tasks. Psychology ranked second with 28.72%, contributing from cognitive, emotional, and behavioral perspectives by analyzing how mental demands affect performance and well-being. Both fields also show the highest h-index values. In third place is Computer Science (13.84%), related to human–computer interaction, interfaces, artificial intelligence, and cognitive simulations. Less dominant but still relevant are specialized areas such as Neuroscience/Neurology (304 articles), which study mental workload through brain function using tools like EEG, fMRI, and neuroimaging; Public Environmental Occupational Health (273), focused on the effects of mental workload on occupational health, psychosocial risk prevention, and well-being policies; and Transportation (252), which examines mental workload in drivers, transit system operators, and road safety. Finally, emerging or complementary areas with growing interest include Behavioral Sciences (172), Science and Technology Other Topics (97), Surgery (83), and Chemistry (80), which explore how mental workload affects decision-making, technical accuracy, and performance in critical environments.

Table 13. Research areas.

R	Area	TP-SV
1	Engineering	1255
2	Psychology	805
3	Computer Science	388
4	Neurosciences Neurology	304
5	Public Environmental Occupational Health	273
6	Transportation	252
7	Behavioral Sciences	172
8	Science Technology Other Topics	97
9	Surgery	83
10	Chemistry	80

Prepared by the authors, based on data from Web of Science (2025). R: Ranking; TP-SV: Number of publications in the search vector; % of 2442: Percentage of articles; h-index: Hirsch index in the search vector; TC-SV: Total articles for the search vector; AC-SV: Average number of citations in the search vector.

3.7. Keywords

From the 6012 keywords used by authors in articles indexed in Web of Science, 75 terms were identified as recurring, each appearing at least 15 times. One of the results of this analysis is shown in Figure 5, where the largest node corresponds to the keyword "mental workload" with 782 occurrences, followed by "workload" and "EEG" (electroencephalogram) with 196 and 144 occurrences respectively (Table 14). The eight clusters formed by these keywords are presented in Table 15. Cluster 1 (red), with 14 terms, focuses on neuroergonomics, simulation, vigilance, and safety, topics relevant to fields such as aviation, associated with keywords like "mental fatigue" and "human error", representing applied studies in critical environments such as healthcare and transportation. Clusters 2 (green) and 3 (light blue) each contain 12 terms. Cluster 2 includes keywords such as "automation", "air traffic control", and measures like "ECG" and "NASA-TLX", reflecting research on human–robot interaction and performance in complex tasks. Cluster 3 includes terms like "augmented reality", "usability", and "cognitive load", indicating a focus on human–computer interaction and user experience, applicable to interface and digital environment design. Cluster 4 (yellow), with 11 keywords, is dominated by neuroimaging techniques such as "EEG", "fNIRS", and working memory analysis, showing its connection to brain activity in cognitive tasks and training, similar to cluster 7 (orange), which explores brain responses to distraction and multitasking. Cluster 5 includes terms related to computational models for evaluating mental workload, while cluster 6 focuses on the impact of mental workload on driving performance. Lastly, cluster 8 (brown), with only 3 terms, reflects recent research on mental workload in healthcare contexts. These findings reveal that research on mental workload is multidisciplinary, spanning neuroscience, psychology, engineering, health, transportation, and digital technology. The clusters help identify specialized subtopics, methodological tools, and key study populations, while also highlighting emerging areas. Among the latter, with only 15 occurrences (the minimum in this analysis), are terms such as "task performance", "task complexity", "human error", "mental fatigue", and "adaptive automation", among others.

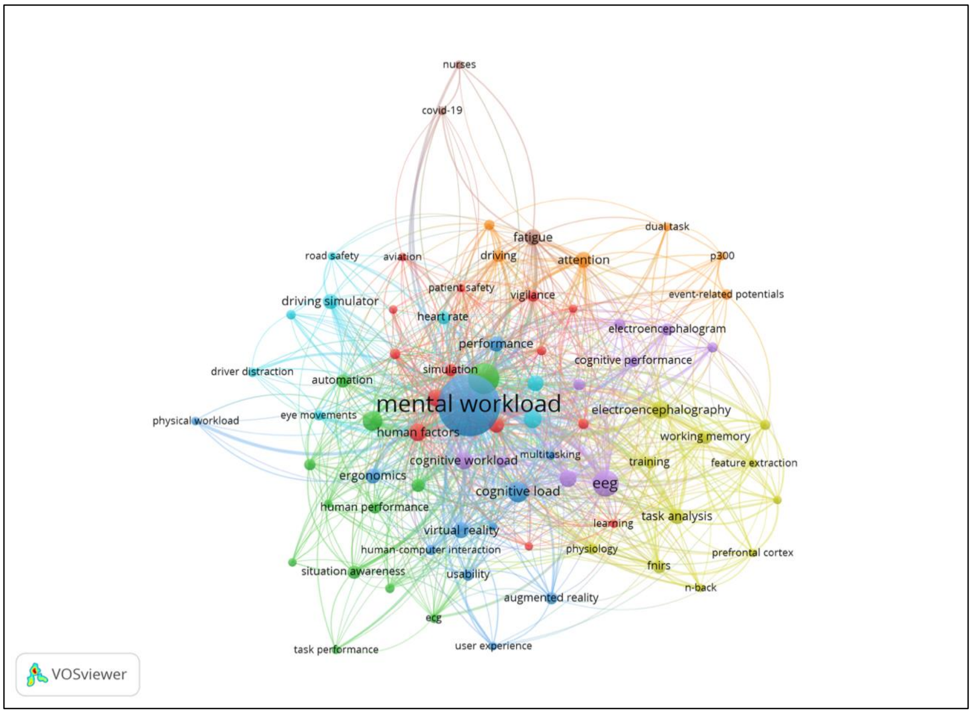

Figure 5. Co-occurrence in the use of author's keywords.

Table 14. Frequency of keyword use.

No.	Keyword	Occurrence
1	mental workload	782
2	workload	196
3	eeg	144
4	cognitive load	88
5	nasa-tlx	86
6	electroencephalography	70
7	heart rate variability	70
8	human factors	68
9	cognitive workload	65
10	machine learning	58

Prepared by the authors, based on data from Web of Science (2025).

Table 15. Co-occurrence clusters in the use of author's keywords.

Cluster 1 (Red-14)	Cluster 2 (Green-12)	Cluster 3 (Light Blue-12)	Cluster 4 (Yellow-11)	Cluster 5 (Purple-9)	Cluster 6 (Calypso-8)	Cluster 7 (Orange-6)	Cluster 8 (Brown-3)
adaptive automation	air traffic control	augmented reality	brain–computer interf	classification	driver distraction	attention	COVID-19
aviation	automation	cognitive	electroencephalograph	cognitive performance	driving performance	distraction	fatigue
cognition	ecg	ergonomics	feature extraction	cognitive workload	driving simulator	driving	nurses
eye tracking	eye-tracking	cognitive load	fnirs	deep learning	eye movements	dual task	
human error	human performance	ergonomics	functional near-infrare	eeg	heart rate	event-related potential	
human factors	nasa-tlx	human–computer intel	n-back	electroencephalogram	heart rate variability	p300	
learning	physiological measure	mental workload	physiology	electroencephalogram	road safety		
mental fatigue	situation awareness	multitasking performance	prefrontal cortex	electroencephalograpl	stress		
neuroergonomics	task complexity	physical workload	task analysis	machine learning			
patient safety	task performance	usability	training				
psychophysiology	workload	user experience	working memory				
safety	human–robot interacti						
simulation vigilance							

4. Discussion

The results of this study answer the initially posed questions, and its objective is achieved by summarizing information from the literature on mental workload.

The scientometric analysis of mental workload (MWL) reveals a significant evolution in scientific production from 1975 to 2024, with a marked increase over the past ten years. This growth reflects not only academic interest in the phenomenon but also its relevance in increasingly demanding and technologically complex work environments (Barreto et al., 2019).

This is consistent with the high number of journals with 0 citations or less than 50 (87.16%), potentially reflecting the publications' increase in recent years and the wide applicability of MWL to different tasks (Longo et al., 2022) and thus suggesting that citations are not concentrated in a handful of journals. The increasing number of studies on MWL validate that the subject warrants further research.

The concentration of publications in fields such as engineering, psychology, transportation, and health suggests that mental workload (MWL) is a cross-disciplinary construct, approached from multiple academic domains. This reflects the broad relevance of MWL across diverse occupational settings and research traditions. The variety of measurement methods such as NASA-TLX, EEG, fNIRS, and ECG, demonstrates a concerted effort to capture the multidimensional nature of the phenomenon. These methods span subjective, physiological, and neurocognitive approaches, each contributing unique insights into how mental workload manifests and affects performance. However, despite the methodological richness, the lack of a universally accepted definition of MWL continues to pose a challenge for theoretical consolidation. The absence of consensus limits the comparability of findings across studies and hinders the development of unified frameworks that could guide future research and practical applications.

The leadership of countries such as the United States, China, and Germany, along with institutions like Sapienza University of Rome and the United States Department of Defense, suggests a geographical concentration of research activity. This observation is consistent with findings by Longo et al. (2022) and applies to scientific research more broadly, where studies indexed in major databases are disproportionately concentrated in high-income countries. Asubiaro et al. (2024), highlights that this imbalance creates a gap in the visibility and representation of scientific output from developing regions. Such disparity underscores the importance of promoting research in underrepresented regions, particularly in Latin America, to enrich the understanding of phenomena from diverse cultural and contextual perspectives.

According to the sample articles, the topic has not been previously addressed through bibliometrics and scientometrics as main methods. Hence, the main strength of this study is its innovative nature. This allows analyzing scientific production and all phenomena related to science communication, which is another strength of this study.

Although the objective of this study was achieved through the application of a valuable tool such as scientometric analysis, this type of study presents limitations from various perspectives that must be considered to avoid biased interpretations. First, these analyses are subject to coverage bias in databases due to the priority most platforms give to certain languages, regions, or disciplines. As a result, articles that could be relevant to the study may be excluded (Taques, 2025). Additionally, the use of databases such as Web of Science or Scopus tends to favor publications in English, leading to an underrepresentation of scientific output in other languages, particularly that produced in Latin America (Camps, 2008). This issue is further accentuated by the fact that this analysis relied on a single database (WoS). One way to overcome these limitations is to use multiple databases; however, this approach is not without challenges, such as the proper handling of selection criteria, applied filters, and the integration of different data sources (Taques, 2025). Moreover, the use of secondary databases is subject to information bias and errors related to classification algorithms, which may result from inaccurate or incomplete data.

In this study, only one search strategy was used, including the term "mental workload", as it is the most precise term representing the construct. However, as Taques (2025) points out, it is possible that authors omit essential information in the metadata of their publications, particularly in abstracts or keywords, which could lead to the exclusion of relevant articles. This omission may negatively affect the visibility of such articles and reduce their citation potential.

5. Conclusions

The findings of this study provide a robust foundation for understanding the current state and emerging trends in research on mental workload. From a theoretical standpoint, and as the first article of its kind addressing this topic, the analysis facilitates the identification of the most influential authors, and the disciplinary domains engaged in the field. This contributes to the conceptual consolidation of the area and highlights existing research gaps.

From a practical perspective, the results offer valuable guidance for future scholarly endeavors. In alignment with this, the study underscores the importance of pursuing further research on mental workload through interdisciplinary and multicultural lenses. A promising avenue for future inquiry could involve examining disruptions in the trajectory of scientific output related to mental workload, alongside conducting a systematic review of the relevant literature. Such efforts would aim to synthesize empirical evidence pertaining to specific dimensions of mental workload, thereby advancing both theoretical understanding and practical application.

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