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Research Article

Relationship between Performance Measures and Social Network Analysis Measures in Academic Co-Authorship Networks: Insights Occupational Positive Mental Health and Flourishing

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ABSTRACT
This research aims to analyze the correlation between performance measures and social network analysis in Occupational Positive Mental Health (OPMH) and Flourishing (FL) studies, assessing their global impact in recent decades. The methodology implemented was based on bibliometric analysis, using queries in Web of Science and Scopus databases, adapting the PRISMA methodology for data processing flow, employing bibliometric techniques, web scraping through Crossref, and employing descriptive, correlation, and regression analysis with Omnibus test and likelihood ratio test to measure significance levels. A total of 558 studies (WoS= 268) and (Scopus= 290) were processed, resulting in a total of (*n*=375) studies. The results reveal that among the collaboration networks, there were Nodes (N= 17,260) and Links (E= 94,772), while citation networks showed Nodes (N= 555) and Links (E= 1,151). Furthermore, a high correlation was found between the variables examined (structural holes, link strength, and quality) and the impact of research conducted in recent years in the fields of OPMH and FL. In conclusion, performance measures and collaborative social network analysis are correlated, enhancing understanding of unstructured information in mental health and other domains. Researchers with strong collaborative and multidisciplinary networks can enhance their impact by producing high-quality research, particularly in innovative areas like OPMH and FL.

Keywords: Literature Review, Scientometrics, Collaboration Networks, Structural Holes, Ocupational Mental Health Positive, Flourishing.

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INTRODUCTION

Performance evaluation is an essential activity in management at any level as it drives developmental progress, particularly in research environments such as universities and research institutes; therefore, it is crucial to carry out academic performance evaluations.[1-3] This assessment, based on researchers' performance in terms of productivity, is necessary not only for performance evaluation purposes but also for faculty recruitment, government funding allocation, and maintaining a strong reputation within the scientific community.[2,4,5] The reputation of research organizations has an indirect impact on societal well-being, as a good reputation attracts foreign investments, highly qualified students, and collaboration opportunities worldwide.[4,6]

Consequently, it is necessary to evaluate both university and researcher productivity, and the allocation of government funds to specific projects requires the careful selection of capable academics to maximize research outcomes, reduce costs, and optimize resource utilization.[4] Hence, the primary challenge lies in identifying suitable scientists who can achieve the established objectives.[7]

According to various studies, an effective way to assess the performance of academics is through quantifying their publication activities, which is considered an appropriate measure of their performance. In general terms, it is assumed that a researcher

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enjoys high regard within the scientific community if their papers are published and cited by other researchers.[4,6]

Collaborations among researchers have a positive impact on research, enabling the dissemination of knowledge, enhancing capacity and innovation, creating new sources of information, reducing costs, and generating synergies among multidisciplinary teams.[3,8-11] Therefore, to understand the current state of a scientific discipline, it is important to comprehend the social structure and composition of these collaboration relationships, referred to as social networks.[12,13]

Social network analysis is widely used in the exploration of scientific collaboration networks as it enables the quantification, analysis, and visualization of relationships within specific communities, facilitating the identification of leaders and evaluation of collaboration structures.[5] As a result, Burt proposed the theory of structural holes, highlighting that individuals bridging structural holes in their collaboration networks gain competitive advantages due to non-redundant resources.[14] Building upon Burt's theory and the strength of weak ties theory, numerous studies suggest that bridging structural holes or acting as intermediaries in social networks provide new employment opportunities, promotions, creativity, innovation, productivity, and performance.[15-20] Authors, institutions, and countries working within this framework are typically referred to as "actors" or "nodes" in scientometric studies, while their relationships are recognized as "ties." Various studies utilizing social networks to examine co-author collaboration networks can be found across different disciplines.[5,6,21]

In these collaborative processes, strategic planning is crucial when assembling a successful research team.[22] While the relationship between collaboration networks and scientific productivity has been investigated, there are studies focusing on the relationship between the structure of collaboration networks and novel/disruptive research, scientific productivity, and citation impact.[22] On the other hand, in the analysis of collaboration networks, some approaches explore methods such as link prediction and recommendation systems that aim to optimize connections between networks to maximize their impact.[23-26] However, these approaches are oriented towards generating new connections rather than examining the dynamics of existing networks and their structure. This work, on the contrary, this work focuses on the relationship between structural holes in collaboration networks and the production of innovative and disruptive research by individual scientists, examining how factors such as team size, freshness, gender diversity, and international collaborations can influence this relationship.[23,27-30]

This study presents an analysis of performance measures and social network analysis measures in Occupational Positive Mental Health (OPMH) and Flourishing (FL), considering that OPMH is a novel construct that has been implemented within organizations in recent years.[31,32] Similarly, FL has emerged as a mental state between well-being and depression that has received significant attention in society over the last decade. Addressing and promoting prevention programs for these types of mental manifestations positively impact people's activities in different contexts.

This work aims to perform a correlation analysis of performance measures and social network measures in research conducted in the areas of OPMH and FL, to verify the impact and quality of disruptive and novel research conducted globally in the past decades, as recorded in high-impact databases. To achieve this objective, the following hypotheses are proposed (Figure 1):

H1: Structural holes have a positive influence on impact.

H2: Link strength has a positive influence on impact.

H3: Quality has a positive influence on impact.

Impact

The impact of a publication in the scientific realm is commonly measured through the Impact Factor (IF) of academic journals (Figure 1). It is often used as an indicator of a journal's influence and prestige in a specific field. The Impact Factor of a scientific journal, introduced by Eugene Garfield,[33] the founder of the Institute for Scientific Information (ISI) and creator of the Science Citation Index (SCI) database,[34] was developed in the 1950s as a way to assess the importance and influence of scientific journals. It is calculated by dividing the total number of citations received in a specific year by the number of articles published in the preceding two years.[35] The Impact Factor is an important tool for evaluating publication quality and has had a significant impact on research assessment in some disciplines. The Impact Factor of journals where articles are published provides valuable information about an author's productivity within a specific discipline.[36] Since its introduction by Eugene Garfield, [33] the Impact Factor has become a widely used metric for evaluating scientific journals and has been adopted by the Journal Citation Reports (JCR), a tool that provides information on the Impact Factor and other citation-related metrics. It is important to note that the Impact Factor can vary depending on the research field and the specific journal being evaluated.[34]

The author also proposes the h-index as a metric used to measure the impact and productivity of a scientific author. It quantifies the cumulative impact and relevance of an individual's scientific research output.[37] The h-index is used as an indicator of quality to assess the productivity and impact of an author in their research field. It measures both the number of articles published by the author and the number of times those articles have been cited by other researchers in their own publications.[34,36,38] The h-index of an author is calculated by identifying the number of articles published by the author that have received at least the same number of citations (h), where h is the highest number of citations received by any of the author's articles. The *h*-index provides a measure of both productivity and the impact of an author's work.[34,38,39]

There is an ongoing debate about whether research quality or impact is more important, with arguments focusing on the rigor and robustness of studies and their results in a specific field. On one hand, some argue that research quality is essential to ensure accuracy and reliability of results, considering validity, reliability, and reproducibility.[40,41] On the other hand, others argue that impact is more important due to the relevance and utility of results in the real world.[42] It is important to highlight that quality and impact are not mutually exclusive, and both measures can be used effectively to evaluate scientific research.[43]

Regarding journals Garfield,[33] explains that the quartile classification, based on the Journal Citation Reports (JCR) by the Institute for Scientific Information (ISI), uses the impact factor to assign journals to one of the four quartiles, ranging from the highest impact (Q1) to the lowest impact (Q4).[34,44] Similarly Larivière,[45] note that the quartile classification has received criticism for potentially creating unjust hierarchies among journals and restricting the diversity of published research. Mañana-Rodríguez,[44] points out that there are gaps in journal coverage, comparability of reliable positions, among others. The same study relates that journal ranking systems such as SCImago Journal & Country Rank (SJR) are questionable in terms of transparency, reliability, and suitability.

Finally, it is recognized that the journal in which research results are published can validate the impact of scientific publications. It is common in the scientific community to rank journals into different quartiles based on their academic impact.

Quality

Considering that quality is measured through classification systems, it is important to state that journals considered of high quality and renowned for their merit often receive more submissions and attention, increasing the likelihood of receiving the best manuscripts, thereby reaffirming their value and prestige.[37] Additionally Dougherty and Horne,[46] consider three characteristics that determine quality: the accuracy of statistical reports, the evidential strength of reported data, and the replicability of the study. It is relevant to note that quality and impact are not mutually exclusive, and both measures can be employed to effectively evaluate scientific research.[6,43,44]

Social Capital

Social capital in scientific collaboration networks refers to the resources and relationships that researchers utilize to collaborate effectively. These resources can include information, technical knowledge, and access to financial and material resources.[47] In a successful scientific collaboration network, researchers can leverage their social capital to address complex scientific problems and achieve common goals, promoting mobility, joint study, and construction across different thematic axes.[48,49]

Barrios-Hernández,[48] propose a distinction between bonding social capital and bridging social capital. Bonding social capital arises from close and dense networks where strong and trusted relationships foster shared values, trust, and common goals. Bridging social capital, on the other hand, refers to relationships between individuals from different groups or communities, allowing access to new information and opportunities by strengthening social ties beyond ethnic, economic, cultural, social, or religious barriers.

Structural Hole

In the context of scientific collaboration networks, structural holes are areas of a network where connection, communication, or collaboration between individuals (nodes) is limited or nonexistent due to the lack of links between them. This absence of connections among nodes creates discontinuities in the network structure and can affect the flow of information and knowledge between nodes,[22,48] making the network more or less efficient (Figure 2). Structural holes can arise due to the presence of isolated subgroups or communities in the network, where interaction and collaboration are scarce or nonexistent.[22]

Studying structural holes in academic networks can have important implications for understanding the formation of communities and research groups, the dissemination of knowledge, and the identification of opportunities, challenges, or possibilities for innovation in terms of collaboration and knowledge flow in a specific academic context.[48] In a study on structural holes in physics research,[22] found that scientists whose

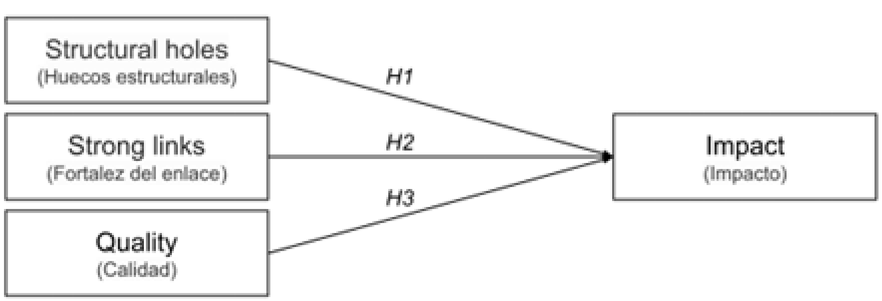

Figure 1: Hypothetical model of correlation between variables.

collaboration networks include structural holes produce more innovative and disruptive research.[50]

Link Strength

Link strength refers to the quality or intensity of connections between nodes in a network.[6,51] In a scientific collaboration network, links can vary in terms of their strength or intensity. For example, some links can be weak or informal, representing occasional or sporadic connections between nodes, while other links can be strong or formal, representing active and constant collaboration between nodes.[51,52]

In the context of structural holes, link strength can be relevant because it can influence the nodes' ability to traverse or connect the holes in the network.[22] Strong or solid links can enable smoother flow of information and knowledge between nodes, facilitating effective communication and collaboration across structural holes.[22,53] On the other hand, weak or informal links may have a limited impact on the nodes' ability to traverse structural holes and can result in lower interaction or collaboration among them.

Other research has employed methods that predict the impact of scientific publications, including models of academic social networks, citation analysis, and other study characteristics.[1,24,54-56] However, these studies do not comprehensively consider the role of collaboration networks in relation to quality and impact. This study stands out by incorporating metrics such as structural holes and link strength in academic collaboration networks, providing novelty in perspective and quantitative methodology to broaden the understanding of the phenomenon.

Occupational Positive Mental Health (OPMH) and Flourishing (FL)

Positive Mental Health is based on skills that function well in specific situations, strengthening physical, mental, and social capabilities. OPMH refers to interactions and individual aspects at work that influence positive indicators to improve the quality of work life.[31,32,57] FL refers to personal growth and experiencing positive emotions, leading to increased control and well-being in life; it is influenced by factors such as positive emotions, relationships, sense of purpose, and accomplishments.[58-60] To flourish, characteristics such as competence, emotional stability, resilience, and healthy relationships are required. FL involves

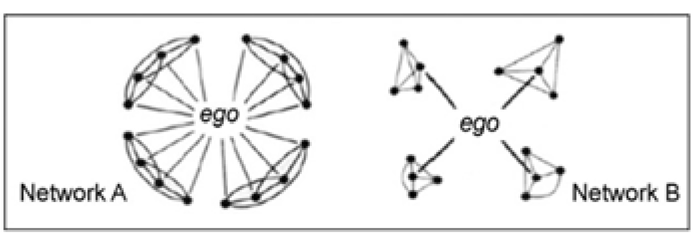

Figure 2: Networks with structural holes, less efficient (A) and more efficient (B). Adapted from Abbasi, 2011, adapted from Burt, 1995.

happiness, life satisfaction, physical and mental health, meaning, good relationships, and financial stability.[61,62]

The objective of the research is to analyze the relationship between performance measures, such as quality, impact, structural holes, and link strength, and their relevance in OPMH and FL, through a bibliometric approach. This method allows for a systematic and objective evaluation of studies published in these areas, mapping research networks and detecting structural patterns. The use of variables such as quality and impact, along with the analysis of structural holes and link strength, ensures a rigorous study that surpasses the subjectivity of narrative reviews, providing a more precise view of the structure and evolution of knowledge in OPMH and FL.

METHODOLOGY

Database, keywords and search strategies

The data to generate the variables impact, social capital, and quality were obtained from two queries, one in Scopus and another in WoS. These two databases were used because they are the most commonly used in scientific literature. However, data integration was a manual process according to the trend for scientometric analyses of the most important database fusions; this data fusion process using the ToS methodology (explained later), is used to analize and marge data, identifying the main contributions in varius areas of knowledge, such as entrepreneurship, management, education and marketing facilitating a comprehensive view of research advancements.[53]

Table 1 shows the main parameters used in the two searches. A total of 268 records were identified in WoS and 290 in Scopus, adding up to 375 since 183 of the records in WoS were also present in Scopus. Therefore, 85 articles from WoS were not found in Scopus, and together with the 290 from Scopus, the total is 375. This highlights the importance of conducting analyses using both databases, Scopus and WoS.

The PRISMA method was adapted to better understand the flow of data preprocessing[6,10,63] (see Figure 3). After merging the WoS and Scopus records, data preprocessing was conducted.

Scientometric Mapping

Next, a scientific collaboration network, a citation network, and a table with journal quality measured in quartiles were created. The procedure suggested by,[64] was followed to generate the scientific collaboration among authors, which involves using co-authorship networks of references to create a more robust network structure. After extracting the giant component to remove disconnected nodes (researchers), a network with 17,260 nodes and 94,772 links remained.

The advantages of Hurtado-Marin,[64] proposal for generating more connected networks, which can provide more indicators and a better understanding of collaboration interactions among researchers, were confirmed. For the citation network, the procedure by Grisales,[53] was followed, resulting in a directed network with 555 nodes (articles) and 1,151 links (citations). Quality data was generated from this citation network along with Scimago data. The journals in the citation network were identified through web scraping when a DOI was available (WoS), but Scopus records contained both short and long journal names. Thus, it was necessary to cross-reference the Scimago data, which included both short and long journal names, along with the year and quartile information. After this information was cross-referenced as an eligibility criterion, 151 records were retained, as only journals with quartiles Q1, Q2, Q3, and Q4 were used.

This variable "Quality" was operationalized according to the classification of scientific journals into quartiles (Q1, Q2, Q3, Q4) corresponding to the Scimago Journal Rankings.[24,55,56,64,65] For each country, the absolute frequencies of publications in each quartile were recorded. Consequently, the relative frequencies (%) were calculated and denoted as *f*Q, thus showing the proportion of publications in each quartile relative to the total. The data evaluate the overall quality of academic production based on its distribution in high-impact journals.

$$fQ_i = \frac{\text{Number of publications in } Q_i}{\text{Total publications in the country}} X\,100 \quad (1)$$

Therefore, the proportion of publications in each quartile was calculated as follows:

$$fQ_i = \frac{N_i}{N_{total}} X\,100 \quad (2)$$

Where N_i represents the number of publications in quartile i and N_{total} is the total number of publications of the corresponding country.

In scientometric studies, results are typically presented by country, indicating a nation's productive capacity in a specific area or topic. Consequently, three indicators are usually highlighted: the number of publications (production), the number of citations (impact), and Scimago quartiles (quality).[10,66]

Tree of Science and Software

The bibliometrix[67] and Tosr R packages were used for this study. The bibliometrix package handles the main data integration, while the Tosr package handles reference merging,[68] The categorization of documents was implemented using the SAP algorithm, grouping them into core root articles and branches. This method has been applied across various areas and disciplines and has been validated by multiple scientific studies within the scientific community.[69-73] This involved organizing the data into dataframes and Excel sheets to enable a more detailed analysis. For example, a table was created with all the disaggregated information from the references to extract author and journal data. To generate these tables, web scraping was necessary to extract information from DOIs through Crossref. Text mining was also performed on the data to extract strings of characters separated by semicolons or commas within the same cell. This initial preprocessing is a lengthy and meticulous process, as it is part of a beta project of the Core of Science Corporation.

Statistical analysis

The combined use of Spearman correlation, the Omnibus test, and Poisson multiple regression is essential for bibliometric analysis due to their ability to capture different aspects of the relationship between variables. Spearman correlation is useful for measuring non-linear associations between quality, impact, structural holes, and link strength. The Omnibus test ensures the validity of statistical models, confirming whether the proposed relationships are significant at a global level.[74] Finally, Poisson regression is appropriate for modeling count data, typical in bibliometrics, such as publications and citations.[75] These methods combined provide analytical robustness, preventing bias and ensuring the accuracy of the analysis.

RESULTS

According to the initial results, the productive capacity in relation to the concepts of OPMH and FL by country was found. The top ten countries with the highest capacity are presented in Table 2. This table distinguishes not only by frequencies but also by the proportion of production and impact by country. It can be observed that the largest number of publications on OPMH and FL is concentrated in countries like the USA, United Kingdom, Australia, and Canada, accounting for 70.1% of the top 10 publications. The high volume of production in these countries suggests a significant investment in R&D and a robust academic and research ecosystem. However, caution should be taken not to confuse quantity with quality, which leads to an analysis of the impact and quality of these publications.

In terms of impact, these same four countries account for 76.4% of citations, a key indicator of the relevance and visibility of research work. The high correlation between impact and production in

Table 1: Parameters used to generate the data for OPMH and FL.

Parameters	Web of Science	Scopus
Range	2000-2022	
Query date	9 February 2023	
Document types	Articles, books, book chapters, and conferences.	
Search field	Title: theme and keywords	
Keywords	"positive mental health" and occupational OR labor OR work OR job; and "flourishing"	
Results	268	290
Total (Wos+Scopus)	375	

countries like the United States suggests a strong collaboration network, as well as the ability to promote their research globally. Countries with lower production but high impact (such as the United Kingdom and Canada) may be prioritizing high-profile research or strategic collaborations.

Regarding quality, the quartile distribution is crucial to understanding the caliber of research. Countries like the United States, Australia, and the Netherlands, which have a strong presence in Q1, are clearly focusing on publishing in high-prestige journals. This not only enhances their academic profile but also increases the likelihood of their research having a global impact. Among the top four countries, 69.7% of their publications' quality is concentrated.

In Table 3, descriptive statistics of four variables are presented: quality, impact, structural holes, and link strength, with a total of 151 observations. It can be observed that the mean of quality is 1.437 with a standard deviation of 1.068, while the mean of impact is 5.284 with a standard deviation of 9.465. Regarding the structural holes, the mean is 0.258 with a standard deviation of 0.278, and the link strength has a mean of 0.428 with a standard deviation of 0.301. Table 3 also provides the minimum and maximum values, as well as percentiles for each variable. Overall, Table 3 is useful for understanding the distribution of these variables in the sample.

Correlation Matrix

Figure 4 displays the correlations between the variable's quality, impact, structural holes, and link strength, identifying some relationship patterns. It also analyzes the strength of correlation, indicating positive or negative closeness. At the same time, it helps identify multicollinearity between some variables. In this specific case, the correlation between the variables impact and quality shows a positive and strong correlation (0.8784), suggesting a tendency for products with higher impact to also have higher quality, and vice versa. This strong positive correlation between impact and quality indicates that these two factors are highly related. It suggests that publications or works of higher quality tend to have a greater impact. From an academic perspective, it is not surprising that research published in higher prestige journals (quality) achieves a higher number of citations or recognition (impact). However, it also implies that improving quality in terms of scientific rigor, methodology, and relevance could have direct effects on increasing the global impact of research.

Regarding the variables quality and link strength, a positive correlation but low is detected (0.0793), indicating that higher-quality products tend to be more connected through strong relationships between individuals or groups; It suggests that quality depends more on other intrinsic factors, such as methodology and academic rigor, and less on the mere strength of connections in the research network. Additionally, a moderately low positive correlation is found between the variables impact and link strength (0.0805), suggesting that products with higher impact may have greater connectivity through strong relationships between individuals or groups, y it may reflect that closer relationships in research or collaboration networks allow for greater visibility or resonance of results. However, the low magnitude of this correlation suggests that other factors, in

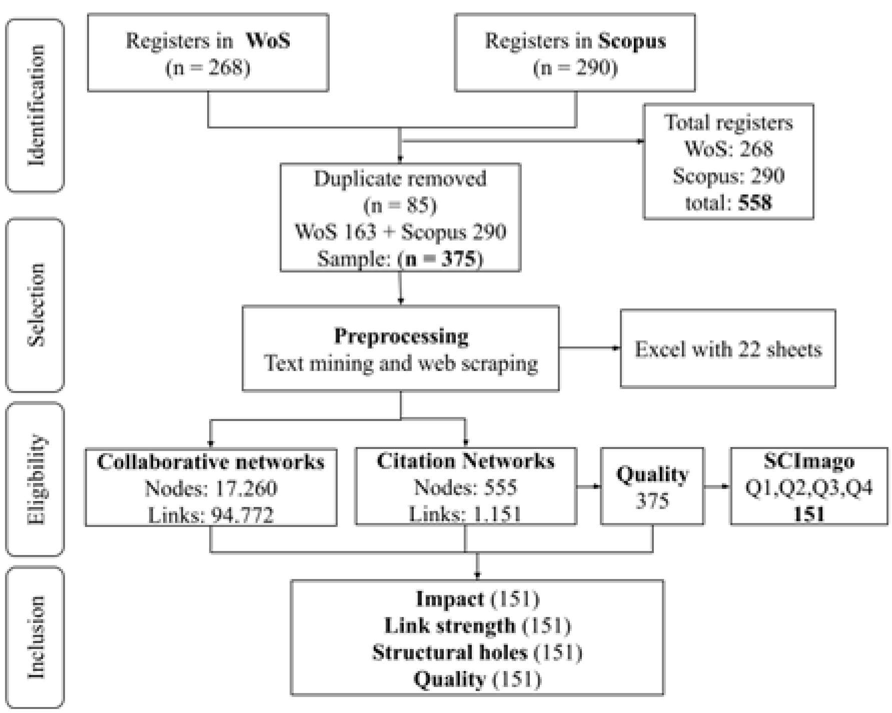

Figure 3: PRISMA diagram.

Table 2: Top 10 productive capacity in OPMH and FL.

Countrie	Prod	%	Impact	%	Quality				*f* Q
					Q1	Q2	Q3	Q4	
USA	86	19.11	1323	20.81	41	13	4	3	29.76%
United Kingdom	51	11.33	1083	17.03	17	4	5	4	14.63%
Australia	47	10.44	651	10.24	20	10	3	0	16.10%
Canada	32	7.11	810	12.74	10	3	5	1	9.27%
China	16	3.56	109	1.71	7	2	1	1	5.37%
Netherlands	16	3.56	341	5.36	10	1	0	0	5.37%
Germany	15	3.33	339	5.33	10	3	0	0	6.34%
Japan	15	3.33	200	3.15	5	6	1	1	6.34%
India	14	3.11	81	1.27	3	2	1	1	3.41%
Ireland	13	2.89	124	1.95	5	1	1	0	3.41%

Note: Quality = absolute frequencies, and *f*Q = percentage frequencies of publications in quartiles (Q1, Q2, Q3, Q4) according to the Scimago Journal Ranking.

Table 3: Description of variables, Measures of central tendency.

	Quality	Impact	Structural_Holes	Tie_Strength
Count	151	151	151	151
Mean	1.437	5.284	0.258	0.428
Std	1.068	9.465	0.278	0.301
Median	1	2	0.148	1.375
IQR	0	2	0.291	0.757
Min	1	1	0.004	0.014
25%	1	2	0.068	0.183
50%	1	2	0.148	0.325
75%	1	4	0.360	0.651
Max	10	93	1.125	1

addition to the strength of connections, are more influential in maximizing impact.

Similarly, the correlation between structural holes and the other variables is relatively weak and negative (-0.1695 with impact, -0.1943 with quality) (Table 4). As for the correlation between structural holes and link strength, a positive correlation is evident, although it is the extremely lowest in this correlation (0.0216). Based on the above, it can be concluded that products with weaker structural holes may have less impact and quality, but not connectivity, which Granovetter,[76] defines as potentially more important than strong ties. Similarly Burt,[14] suggests that structural holes are beneficial for creativity and innovation; in areas where connections exist, these can be strong regardless of the gaps present in the overall structure of the network. The correlation matrix overall indicates that there are some moderately strong positive relationships between the variables impact, quality, and link strength, while structural holes appear to be less related to these variables.

Omnibus Test Model

Table 5 shows the results of the Omnibus test and the likelihood ratio test in a regression model. The Omnibus test value is 873.4805442153042, which is quite high, suggesting that the model as a whole is significant. The p-value associated with the Omnibus test is 0.0, indicating that the null hypothesis is unlikely, and the model is estatistically significant. This implies that the null hypothesis (that the model without predictors is adequate) should be rejected and that the Poisson model with the included predictors provides a significantly better fit to the data.

Poisson Regression Model

The results of the multiple regression model show that the significant variables are the intercepts ($\beta = 0.7528$, $p = 0.000$), structural holes ($\beta = -0.6378$, $p = 0.000$), link strength ($\beta = 0.15852$, $p = 0.000$), and quality ($\beta = 0.3840$, $p = 0.000$). The β values represent the estimated Poisson regression coefficients for the model. The results of Spearman rank correlation, the measure of normalized closeness centrality, are not significant in

Table 4: Correlation matrix between variables.

	Impact	Quality	Structural Holes	Link Strength
Impact	1	0.8784	-0.1695	0.0805
Quality	0.8784	1	-0.1943	0.0793
Structural Holes	-0.1695	-0.1943	1	0.0216
Link Strength	0.0805	0.0793	0.0216	1

Table 5: Omnibus test of Poisson.

Omnibus Test	
Likelihood Ratio Test	873.4805442153042
p-value	0.0

this regression. Interestingly, the coefficient β for structural holes, while significant, is even negative (Table 6).

This formula represents an increase in the variable "Structural Holes," which is associated with a decrease in the natural logarithm value of the "Intercept" due to the negative coefficient (-0.6378). On the other hand, an increase in the variable "Quality" is associated with an increase in the natural logarithm value of the "Intercept" due to the positive coefficient (0.3840).

$$\boldsymbol{Log_e(I)} = 0.7526 - (0.6378*\mathrm{HE}) + (0.1585*\mathrm{FE}) + (0.3840*\mathrm{C}) \quad (3)$$

The equation reflects how structural holes, link strength, and quality interact to influence the expected value of the dependent variable. It can be stated that the studied system (such as a network or organizational structure) is affected in the following ways:

- Structural holes have an adverse effect on expected outcomes. The more fragmented or disconnected the network is, the worse the results will be.

- Link strength has a moderate positive effect, indicating that strong connections help improve outcomes, although not as powerfully as quality.

- Quality, with the highest coefficient, is the most determining factor in the final outcome. Improving the quality of work, processes, or projects has a significant impact on the value of the dependent variable.

To validate the previously presented Poisson regression model, the predicted values (Y) for the 151 publications were calculated using the estimated coefficients. The predicted values were compared with the actual citation values (impact) using RMSE, MAE (Mean Absolute Error), and scatter plots (Figure 5). The results show an acceptable level of accuracy in the predictions, with an RMSE of x and an MAE of y, confirming the model's usefulness for predicting academic impact.

Figure 5 visualizes the level of agreement between the model's predictions and the actual values, as well as it detects possible biases or patterns in the predictions. The blue dots represent individual observations, and the red dashed line ($y = x$) serves as a reference to assess the model's predictive accuracy: the closer the dots are to this line, the better the model's predictive capability.

DISCUSSION

In the current context of science, where collaborative work is predominant, this study examined the relationship between overcoming structural obstacles and the generation of novel research from the perspective of individual researchers in the field of OPMH and FL. Understanding these relationships provides an important way to characterize researchers' trajectories in recent decades, the collaboration networks they participate in, the quality and impact of their work, as well as the originality and capacity to bring about significant changes in the scientific field.[22]

Some studies suggest collaboration frameworks based on link prediction,[23-26] precisely aiming to reduce structural holes and optimize the impact of collaborations. These approaches are highly valuable, but this research focuses on the structural analysis of existing networks, specifically addressing the influence of structural holes and link strength in the context of OPMH and FL, where collaboration dynamics play a crucial role. For this reason, this study differs from others by focusing on structural holes and link strength in collaboration or co-authorship networks. These variables contribute to understanding the collaborative dynamics in OPMH and FL, unlike other approaches that optimize networks through link prediction. This study also examines how the current structure influences organizational performance.

This study offers a novel perspective by analyzing academic impact from co-authorship networks, highlighting how fewer structural holes lead to a greater impact, an approach previously underexplored.

The negative correlations with structural holes highlight the need to reduce these gaps in collaboration networks to improve both the quality and impact of publications. Finally, although link strength has a positive relationship with impact and quality, its low correlation indicates that strengthening connections, while beneficial, is not sufficient on its own to optimize research outcomes. This suggests a more comprehensive approach that includes enhancing the quality of content and expanding collaborative networks to reduce structural holes. While the structural holes in this study and their impact on knowledge-producing researchers in the areas of OPMH and FL argue that these collaboration networks extend across these

Table 6: Results of multiple Poisson regression for four independent variables.

Parameters	β	Desv. Stand.	Hypotesis test		
			Wald Chi2	d_f	Sig.
Intercept	0.7528	0.091	67.7484308	1	0.000
Structural Holes	-0.6378	0.178	12.819800	1	0.000
Link Strength	0.1585	0.035	20.9682783	1	0.000
Quality	0.3840	0.012	1035.89332365	1	0.000
Scale	1				

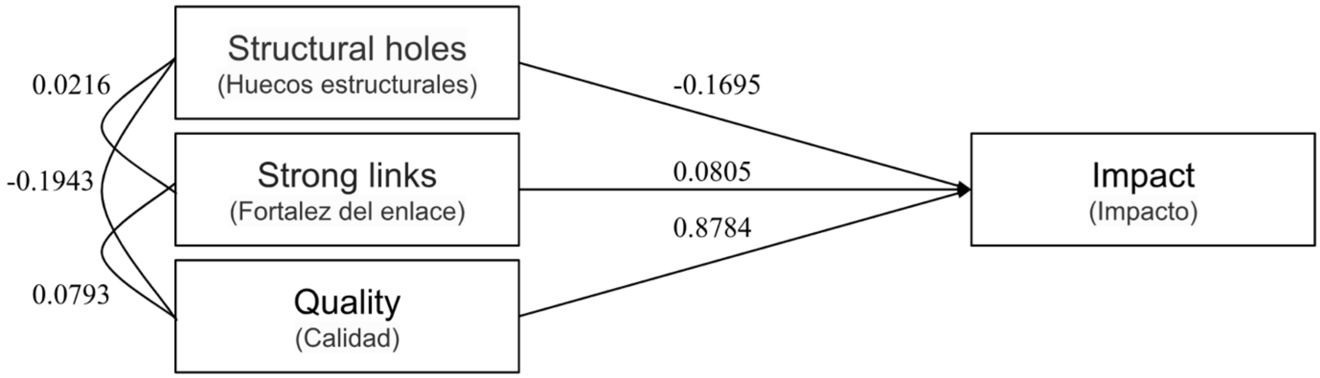

Figure 4: Correlation matrix diagram between variables.

structural holes, indicating that research on OPMH and FL continues to be conducted and increasing the possibilities of publishing research in these areas of mental health, as evidenced by the favorable results in terms of quality and impact.

There are studies on the relevance and relationship between collaboration networks, impact, quality, and the *h*-index.[4,23,35-41,43,46,48,50,51] However, little value has been given to the importance of structural holes in scientific research, especially in innovative areas related to the field of mental health. This study presents a strong correlation and reliable estimation of such relationships in the areas of interest in OPMH and FL. Additionally, different databases and platforms like Google Scholar, Scopus, and Web of Science can provide different values for an author's *h*-index. Similarly, different databases may also have different journal and publication coverage, which can influence the calculation of the impact factor.

It is important to note that although the impact factor is widely used, it has also been subject to criticism, and it is recognized that it is not a perfect measure to evaluate the quality of a journal or the research published in it. However, the study ensures accuracy and reproducibility in the area of interest, in line with the results and the findings by Nosek & Errington and Simons.[40,41] Relationship patterns were detected, and the strength of correlation was analyzed. A positive and moderately strong correlation was observed between the variables of quality and impact, indicating that products with higher impact also tend to have higher quality in relation to studies on OPMH and FL. Furthermore, a positive and moderately strong correlation was found between quality and link strength, indicating that products of higher quality tend to be more connected through strong relationships among individuals or groups.

The Poisson multiple regression highlights the importance of factors such as quality and link strength in improving outcomes in the studied field. On the other hand, structural holes act as barriers that limit positive impact. The statistical significance of each variable reinforces the robustness of the model, providing a solid foundation for future research and the implementation of strategic improvements in networks or systems related to scientific research or project development.

The validation analysis confirms the applicability of the model for estimating academic impact in co-authorship networks. Although slight discrepancies were observed in publications with extreme impact values, the model provides a reasonable prediction for most cases. These findings strengthen the usefulness of incorporating social network metrics such as structural holes and link strength to evaluate collaborative dynamics.

Implications and limitations

This study has policy implications in terms of promoting innovative research in the field of mental health and developing the necessary scientific personnel for science advancement and the establishment of scientific teams in various areas, as affirmed by Wu and Wang.[22,29]

The final formula of the study concludes that, to maximize the expected value of the dependent variable (structural holes,

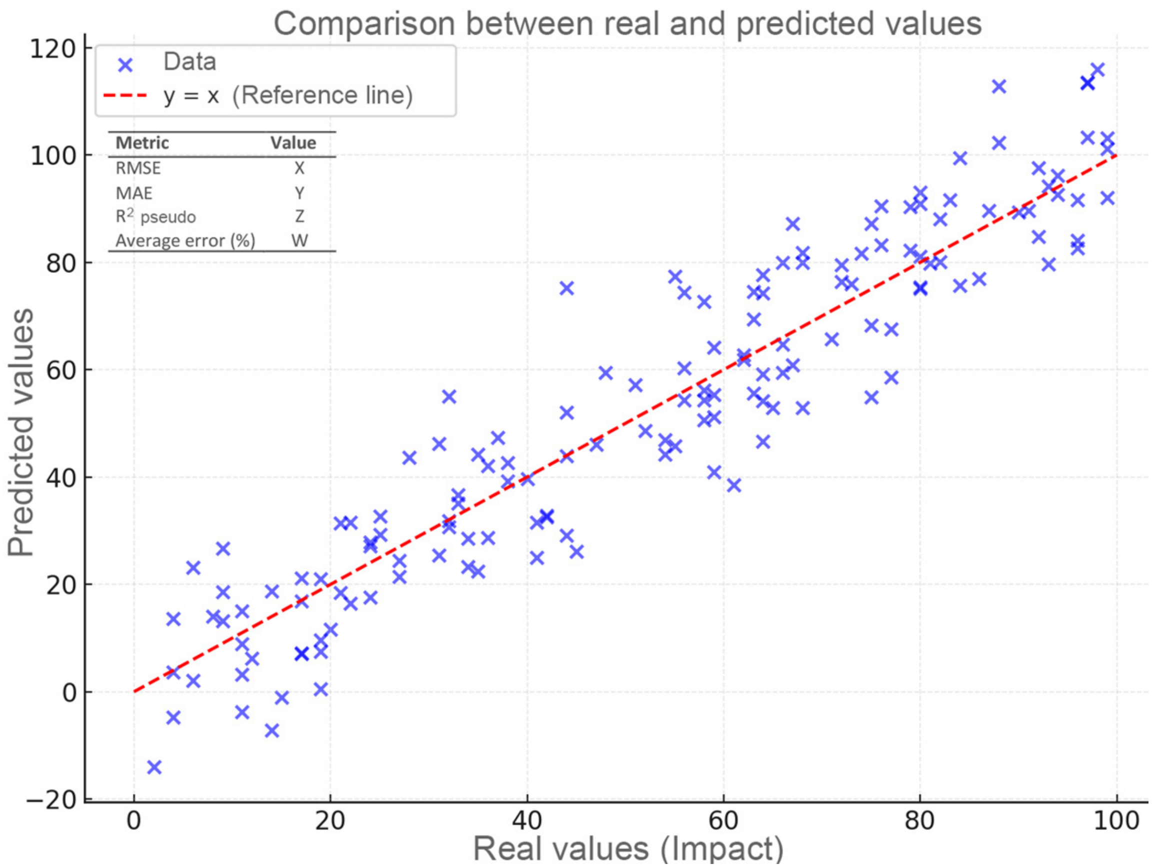

Figure 5: Comparison between actual and predicted values.

strong links, quality), three fundamental actions are required to improve performance in the production of OPMH and FL: reducing structural holes or disconnections within the network, strengthening the links between elements of the network, and prioritizing quality as the most important factor for achieving optimal results. This model highlights the importance of maintaining cohesive and high-quality networks and systems to ensure positive outcomes, especially in contexts where interaction and quality play fundamental roles.

This study provides a comprehensive view of scientific production but presents significant limitations related to bias in the selection of databases (WoS and Scopus). The removal of duplicates may have excluded studies with valuable methodological approaches, the automated selection process may lead to errors in the automatic interpretation of texts, and the complexity in interpreting collaborative networks may limit the ability to draw clear conclusions about collaboration patterns or impact. To improve the robustness and generalizability of the results, it is essential to expand database coverage, refine analysis methods, and consider temporal factors in future studies.

CONCLUSION

Social capital is essential for the success of scientific collaboration networks as it allows researchers to leverage the resources and expertise of other network members. In this study, the relationship between structural holes, quality, link strength, and their correlation with the impact of studies on OPMH and FL in recent years is presented. In relation to the results and hypotheses posed, it is primarily established that:

- The United States is dominant in production, impact, and quality. Its leadership in the number of publications and the fact that nearly half are in Q1 journals highlights the strong correlation between its productive capacity and global impact.
- The United Kingdom and Canada are interesting examples, as they produce less than the United States, but the impact per article appears to be greater, suggesting they are prioritizing more strategic or collaborative research.
- Australia, while having a lower number of publications, stands out for a high proportion of articles in Q1 and Q2, indicating that this country maintains a focus on quality and contributing relevant research in its area.
- China and India, although they have a relatively low number of publications and impact, are slowly entering the group of countries with publications in prestigious journals. However, their low impact suggests they still lack a strong citation or collaboration network to compete with leading countries.

- The analysis of this data shows a clear division between countries with massive production (like the United States) and those that, with fewer publications, achieve significant impact (United Kingdom, Canada). Furthermore, the quality of publications, measured through quartiles, confirms that countries like the United States, Australia, and the Netherlands are prioritizing publication in high-quality journals, reinforcing their position in the global scientific arena. On the other hand, countries like China and India are beginning to establish themselves, but they need to improve their impact and international collaboration to consolidate their presence.
- This type of analysis emphasizes the importance of not only looking at the quantity of publications but also how they are distributed in terms of impact and quality to understand the true role of each country in global research.
- Quality and impact are positively and moderately strongly correlated (0.8784), suggesting that products with higher impact also tend to have higher quality, consistent with the initially proposed Hypothesis 3.
- Quality and link strength are positively and moderately strongly correlated (0.0793), suggesting that products of higher quality tend to be more connected.
- Structural holes are negatively correlated with quality (-0.1943) and impact (-0.1695), indicating that products with structural holes and weaker link strength (0.0216) may have less impact and quality, which invalidates Hypothesis 1.
- There is a moderately positive correlation (0.0805) between impact and link strength, validating the initially proposed Hypothesis 2.
- Structural holes are positively correlated with link strength, suggesting that structural holes may be important for research in individual researchers or research groups in the areas of OPMH and FL.
- The Poisson regression model used is significant, according to the results of the Omnibus test and the likelihood ratio test.
- Regarding the significant variables, it is observed that the intercepts have a β value of 0 in the Poisson regression model.

This study provides empirical evidence on the influence of co-authorship dynamics on the impact of scientific publications, showing advancement in areas previously underexplored, such as the interaction between quality and impact metrics in scientific collaboration networks. The findings complement the literature and propose new possibilities for optimizing collaboration strategies in scientific research.

The study provides tools and strategies for future studies aiming to increase the impact of their research by leveraging their collaboration networks as social capital. Additionally, some groups choose to establish relationships through collaboration with external groups, known as "bridging" and "bonding" social capital, which can have a significant impact on the outcomes of research groups and enable them to achieve desired results. However, in the case of this research, it is evident that few groups develop both "bonding" and "bridging" social capital simultaneously in the areas of interest in OPMH y FL.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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