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Mapping Technology Transfer Networks in the Agroindustry: A Social Network Analysis of Peru, Colombia, and Mexico

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***Abstract*—Technology transfer in agroindustry is shaped by the circulation of scientific knowledge among researchers, institutions, and countries. In Latin America, these relationships remain uneven, which may limit the diffusion of innovations across agroindustrial value chains. This study applies Social Network Analysis (SNA) to examine citation networks associated with agroindustry-related research in Peru, Colombia, and Mexico. Bibliometric records retrieved from Scopus for the period 2000–2024 were organized into three analytical levels: authors, organizations, and countries. Degree centrality, betweenness centrality, clustering coefficient, density, and network diameter were used to identify influential actors, bridging positions, and cohesion patterns. The results indicate that knowledge circulation is concentrated around a reduced group of authors, institutions, and countries. The organizational layer shows greater fragmentation than the author and country networks, suggesting weaker institutional articulation in the citation structure. These differences reveal collaboration capacities and structural gaps that may affect the dissemination of agroindustrial knowledge. The study provides evidence for strengthening institutional linkages, promoting cross-country collaboration, and orienting funding strategies toward more balanced technology transfer networks in the Latin American agroindustrial sector.**

***Keywords*—technology transfer, agroindustry, social network analysis, innovation networks, latin america**

I. Introduction

The agroindustrial sector provides an appropriate setting for examining technology transfer because it links scientific knowledge, productive capabilities, rural development, and sustainability challenges. In Latin America, agroindustrial competitiveness depends not only on the availability of technologies, but also on the capacity of firms, universities, research centers, and public agencies to exchange knowledge and coordinate innovation activities [1]–[3]. Recent studies on agri-food and agroindustrial innovation show that technology transfer is shaped by university–industry relations, extension services, innovation brokers, producer networks, and institutional arrangements that enable knowledge circulation [4]–[7].

However, knowledge flows in agroindustrial systems remain uneven. Weak interaction among research organizations, firms, producer associations, and policy actors can delay technology adoption, limit collective learning, and reinforce asymmetries between central and peripheral actors [8]–[10]. These constraints are particularly relevant for small and medium-sized producers, which often require technical knowledge, market information, and collaborative innovation mechanisms to participate in higher-value agroindustrial chains [11]–[13].

Social Network Analysis (SNA) offers a suitable methodological approach for examining these relational structures. Rather than focusing only on the attributes of individual actors, SNA analyzes how actors are connected and how their positions influence knowledge diffusion. In agricultural and rural innovation studies, this approach has been used to identify central actors, brokerage positions, cohesive groups, and structural gaps that affect technology diffusion and collective action [9], [14], [15]. Metrics such as degree centrality, betweenness centrality, clustering coefficient, density, and network diameter allow the analysis of knowledge concentration, bridging roles, local cohesion, and possible restrictions in information flows [16]–[18].

Although previous research has examined agricultural innovation networks, university–industry technology transfer, and collaboration in Latin American science systems, fewer studies have combined bibliometric evidence with a multi-level network analysis focused on agroindustry-related research. Existing contributions usually examine individual countries, specific commodities, or a single level of interaction, such as authors, institutions, or countries [1], [10], [19]. This leaves an empirical gap regarding how citation-based knowledge flows are structured across different analytical layers and how these layers reveal patterns of concentration, cohesion, and fragmentation.

This study addresses that gap by mapping and interpreting technology transfer networks in agroindustry-related research associated with Peru, Colombia, and Mexico. These countries were selected because they represent relevant Latin American cases for analyzing agroindustrial knowledge flows, participate in regional research and innovation dynamics, and provide sufficient bibliometric representation for comparative network analysis. The study uses Scopus records from 2000 to 2024 and examines three network layers: authors, organizations, and countries.

The objective of the study is to analyze the structure of citation networks related to technology transfer in agroindustry across Peru, Colombia, and Mexico. Specifically, the study seeks to: (i) identify influential authors, organizations, and countries; (ii) examine bridging positions and cohesive groups; (iii) compare cohesion and fragmentation across the three network levels; and (iv) derive implications for strengthening regional collaboration and technology transfer policies in agroindustrial innovation systems.

The remainder of the paper is organized as follows. Section II reviews the literature on technology transfer, innovation networks, and SNA in agroindustrial contexts. Section III describes the data source, search strategy, network construction, and analytical metrics. Section IV presents the results for the keyword, author, organization, and country networks. Section V discusses the implications of the findings for regional collaboration and policy and presents the study limitations. Finally, Section VI summarizes the main conclusions and future research directions.

II. Literature Review

A. Technology Transfer in the Agroindustry

Technology transfer in agroindustry refers to the adaptation, circulation, and use of scientific knowledge, technical capabilities, and organizational practices in productive environments. It includes, but is not limited to, research commercialization, extension services, collaborative projects, knowledge exchange, innovation brokerage, and learning processes among universities, firms, public agencies, and producers [4]–[6]. In agroindustrial systems, these mechanisms are particularly relevant because technological change depends on interactions among research organizations and actors located along value chains, including small and medium-sized producers, processors, exporters, and sectoral institutions [7], [11], [20].

In Latin America, technology transfer is affected by institutional fragmentation, limited absorptive capacity, weak university–industry linkages, and unequal access to technical knowledge [1], [2], [21]. These constraints influence the diffusion of innovations in sustainable production, irrigation, post-harvest management, traceability, and agroindustrial processing. Therefore, the study of technology transfer requires attention not only to individual organizations, but also to the relational structures that connect scientific, productive, and policy actors [10], [13].

B. Innovation Networks and Regional Collaboration

Innovation networks are formed by relationships through which actors exchange knowledge, resources, information, and capabilities. In agricultural and agroindustrial contexts, these networks support collective learning, reduce uncertainty, and facilitate technology adoption when they connect heterogeneous actors with complementary capacities [8], [9], [12]. Their performance depends on the quality of interactions, the diversity of participants, and the presence of actors capable of linking otherwise disconnected groups [7], [15].

Regional collaboration is relevant in Latin America because agroindustrial challenges often exceed national boundaries. Food security, climate adaptation, sustainable production, export competitiveness, and value-chain upgrading require coordinated responses among countries, research institutions, and productive sectors [3], [22]. However, collaboration networks may reproduce asymmetries when knowledge flows are concentrated around a small group of central actors or institutions. Identifying these concentrations is necessary for designing policies that strengthen peripheral actors and improve knowledge circulation across regions [1], [18].

C. Social Network Analysis as an Analytical Tool

Social Network Analysis (SNA) provides a methodological framework for examining the structure of relationships among actors. Rather than focusing only on the attributes of researchers, institutions, or countries, SNA analyzes how actors are connected and how their positions influence knowledge circulation [16], [17]. In agricultural innovation studies, SNA has been used to identify central actors, brokerage roles, cohesive groups, and structural gaps that affect technology diffusion and collective action [10], [14], [18].

Several indicators are commonly used in this type of analysis. Degree centrality identifies actors with many direct connections, while betweenness centrality detects actors that link different parts of the network. The clustering coefficient measures the tendency of connected actors to form cohesive groups, and network diameter indicates the maximum distance between nodes [23], [24]. These metrics support the interpretation of knowledge flows as concentrated, dispersed, cohesive, or dependent on a reduced number of bridging actors.

Bibliometric network analysis also depends on specialized software. VOSviewer supports the construction and visualization of bibliometric maps, especially keyword co-occurrence and citation networks [25]. Gephi enables the exploration, visualization, and calculation of structural indicators in complex networks [26]. In addition, modularity-based algorithms are widely used to detect communities and interpret thematic, institutional, or regional groupings within networks [27].

D. Synthesis of the Literature

Table I summarizes the main literature streams that support this study and their contribution to the analysis of technology transfer networks in agroindustry.

E. Identified Research Gap

The literature shows increasing interest in technology transfer, agricultural innovation systems, and social networks in Latin America. However, existing studies commonly focus

TABLE I: Main Literature Streams Supporting the Study

Literature stream	Main contribution	Use in this study
Technology transfer and university–industry relations	Explains how knowledge moves from research environments to productive sectors through collaboration, engagement, and commercialization mechanisms [4]–[6].	Supports the interpretation of citation networks as evidence of knowledge circulation among scientific and institutional actors.
Agricultural and agroindustrial innovation systems	Emphasizes systemic interaction, innovation brokerage, extension mechanisms, and collective learning in agricultural and agroindustrial contexts [7], [8], [11].	Provides the conceptual basis for analyzing technology transfer beyond individual actors and considering value-chain relationships.
Social Network Analysis in agricultural innovation	Identifies central actors, brokers, cohesive groups, and structural gaps affecting technology diffusion and collaboration [9], [10], [14].	Guides the selection and interpretation of centrality, clustering, density, and cohesion indicators.
Bibliometric and network visualization methods	Provides tools and algorithms for mapping citation, co-occurrence, and community structures [25]–[27].	Supports the use of VOSviewer, Gephi, and modularity-based community detection in the empirical analysis.

on individual countries, specific commodities, or single levels of analysis, such as producers, institutions, or national scientific systems [1], [19], [28]. Less attention has been given to citation-based technology transfer networks that simultaneously examine authors, organizations, and countries in agroindustry-related research.

This gap is relevant because each analytical level captures a different dimension of knowledge circulation. Author networks identify influential researchers and citation patterns. Organization networks reveal institutional concentration or fragmentation. Country networks show regional and international knowledge flows. An integrated analysis of these three levels can provide a more complete understanding of the structure of agroindustrial technology transfer in Peru, Colombia, and Mexico.

III. Methodology

A. Research Design

This study applies a bibliometric network approach to examine citation-based technology transfer networks in agroindustry-related research associated with Peru, Colombia, and Mexico. The methodological design combines bibliometric data extraction with Social Network Analysis (SNA), allowing the identification of influential actors, brokerage positions, cohesive groups, and structural gaps across three levels of analysis: authors, organizations, and countries [10], [14], [18]. This approach is appropriate for studying technology transfer because knowledge circulation depends not only on individual actors, but also on the relational structure through which scientific and institutional connections are formed [4]–[6].

B. Data Source and Search Strategy

Bibliometric records were retrieved from Scopus. This database was selected because it provides standardized metadata on authors, affiliations, countries, citations, abstracts, keywords, and references, which are required for bibliometric and network analysis [25]. The search strategy was designed to capture literature related to technology transfer, university–industry relations, and agroindustrial innovation.

To improve the thematic coverage of the dataset, the search expression included terms related to technology transfer, knowledge transfer, university–industry collaboration, agriculture, agribusiness, agri-food systems, and agricultural innovation. This decision responds to the interdisciplinary nature of agroindustry, which is commonly addressed in agricultural sciences, environmental sciences, engineering, business, and social sciences [7], [8], [11]. The initial Scopus query was:

```
TITLE-ABS-KEY(("technology transfer" OR
"knowledge transfer" OR "university-industry
collaboration") AND (agroindustry OR
agribusiness OR agriculture OR "agri-food"
OR "food system*" OR "agricultural
innovation") AND (Peru OR Colombia OR
Mexico))
```

After the initial search, the dataset was restricted to records published between 2000 and 2024. The selection was then limited to peer-reviewed journal articles. Conference papers, book chapters, editorials, notes, and other non-article documents were excluded. Duplicate records and entries with incomplete authorship or affiliation metadata were removed before constructing the networks.

Table II summarizes the data selection protocol used in the study.

TABLE II: Data Selection Protocol

Criterion	Description
Database	Scopus
Period	2000–2024
Document type	Peer-reviewed journal articles
Search fields	Title, abstract, and keywords
Thematic focus	Technology transfer, knowledge transfer, university–industry collaboration, agroindustry, agribusiness, agriculture, agri-food systems, and agricultural innovation
Geographic focus	Peru, Colombia, and Mexico
Exclusion criteria	Duplicates, non-article documents, records outside the study period, and records with incomplete authorship or affiliation metadata

Table III reports the filtering process applied to the Scopus export and the final analytical units used to construct the author, organization, and country networks.

The initial Scopus export contained 53 records. After restricting the dataset to the 2000–2024 period, 37 records remained. The selection was then limited to peer-reviewed journal articles, resulting in 25 records. No duplicate records were identified based on EID, DOI, and title. One record was excluded because it lacked complete affiliation metadata.

The final dataset therefore included 24 articles for network construction.

TABLE III: Dataset Filtering and Final Analytical Units

Selection stage / analytical unit	Number
Initial Scopus records retrieved	53
Records after year filtering, 2000–2024	37
Records after document-type filtering, articles only	25
Records after duplicate removal	25
Records excluded due to incomplete metadata	1
Final articles included in the analysis	24
Author-network nodes	57
Author-network edges	432
Organization-network nodes	26
Organization-network edges	40
Country-network nodes	46
Country-network edges	541

C. Data Processing

For each record, metadata on authors, institutional affiliations, countries of origin, citation links, titles, abstracts, and keywords were extracted. Author names and institutional affiliations were reviewed to reduce inconsistencies caused by spelling variations, abbreviations, and different institutional naming conventions. Country names were standardized according to the affiliation metadata provided in Scopus.

The dataset was organized into three analytical layers. The author layer captured citation relationships among researchers. The organization layer represented citation flows among institutional affiliations. The country layer aggregated citation relationships according to the countries associated with the authors' affiliations. This multi-level structure allows the comparison of knowledge circulation at individual, institutional, and national scales [1], [9], [23].

Although the empirical search focused on Peru, Colombia, and Mexico, the country-level network includes all countries identified in the citation relationships derived from the retrieved corpus. Therefore, countries outside the three focal cases may appear as influential nodes when they occupy central positions in the broader citation structure.

D. Network Construction

Three directed citation networks were constructed. In directed networks, an edge represents the direction of a citation from one node to another. This distinction is relevant because citation flows are not necessarily reciprocal and may reveal asymmetric patterns of visibility, influence, or dependence within the scientific field.

Table IV presents the criteria used to construct each network layer.

TABLE IV: Network Construction Criteria

Network layer	Node	Edge	Analytical purpose
Author network	Individual author	Citation from one author to another	Identifies influential researchers and citation-based knowledge hubs
Organization network	Institutional affiliation	Citation from one organization to another	Examines institutional concentration, fragmentation, and brokerage positions
Country network	Country of affiliation	Citation flow between countries	Analyzes international knowledge circulation and regional collaboration patterns

E. SNA Metrics

The analysis used standard SNA indicators to describe influence, cohesion, brokerage, and structural fragmentation [16]–[18]. Degree centrality was used to identify nodes with a high number of direct connections. Betweenness centrality was used to identify actors that connect otherwise separated parts of the network. Closeness centrality measured how near a node is to the rest of the network. Density and clustering coefficient were used to evaluate cohesion, while diameter measured the maximum distance between connected nodes.

Table V defines the metrics used and their interpretation in this study.

TABLE V: SNA Metrics Used in the Study

Metric	Definition	Interpretation in this study
Degree centrality	Number of direct connections of a node	Identifies authors, organizations, or countries with high direct citation activity
Betweenness centrality	Frequency with which a node lies on the shortest path between other nodes	Detects bridging actors that connect otherwise separated groups
Closeness centrality	Inverse of the average distance from one node to all other reachable nodes	Indicates how efficiently a node can reach the rest of the network
Density	Proportion of existing links relative to all possible links	Evaluates the overall level of connectivity in each network
Clustering coefficient	Proportion of links among the neighbors of a node	Measures the tendency to form cohesive local groups or communities
Diameter	Longest shortest path between two connected nodes	Indicates the maximum distance required for knowledge to circulate across the network
Modularity	Degree to which the network can be divided into communities	Identifies thematic, institutional, or regional clusters within the network

F. Software and Visualization

Keyword co-occurrence analysis was conducted using VOSviewer, which supports the construction and visualization of bibliometric maps based on co-occurrence, citation, and co-authorship relationships [25]. Network processing, metric calculation, visualization, and community detection were performed in Gephi, an open-source platform for analyzing complex networks [26]. Community structure was examined using a modularity-based algorithm, which identifies groups of nodes that are more densely connected internally than with the rest of the network [27].

In the visualizations, node size represents the relative importance of each node according to centrality values, edge direction represents citation flow, and node color indicates community membership when applicable. These graphical criteria were applied consistently to facilitate comparison across the author, organization, and country networks.

G. Methodological Limitations

The methodology has three limitations. First, the use of Scopus may exclude relevant regional publications, technical reports, policy documents, and grey literature that are not indexed in the database. Second, citation networks capture academic visibility, but they do not directly measure technology adoption or practical transfer to firms and producers. Third, the networks are analyzed as aggregated structures for the 2000–2024 period; therefore, temporal changes in collaboration patterns are not examined. Future research could address these limitations by incorporating additional databases, patent records, project data, interviews, and longitudinal network analysis.

IV. Results

A. Keyword Co-Occurrence Analysis

The keyword co-occurrence analysis identified the main thematic areas associated with technology transfer, university–industry collaboration, and agroindustrial innovation. The records retrieved from Scopus were processed in VOSviewer, following the search strategy described in Section III. This procedure grouped recurring terms and identified thematic concentrations within the dataset [25].

Keywords were extracted from titles, abstracts, and author-defined keywords. A minimum occurrence threshold of five was applied to reduce isolated terms and retain concepts with repeated presence in the corpus. In the resulting network, nodes represent keywords, node size indicates frequency, edges represent co-occurrence in the same document, and colors indicate clusters identified through community detection procedures [27].

Figure 1 presents the keyword co-occurrence network generated from the Scopus dataset for the 2000–2024 period.

The network shows four main thematic clusters. The first cluster groups terms related to entrepreneurship, spin-offs, incubators, startups, and academic entrepreneurship. The second cluster is associated with patents, inventions, faculty involvement, contracts, and productivity. The third cluster includes policy frameworks, methodology, stakeholders, barriers, and diffusion. The fourth cluster is linked to university–industry collaboration, absorptive capacity, efficiency, and collaborative research. These clusters indicate that technology transfer research connects entrepreneurial mechanisms, intellectual property, policy instruments, and collaborative innovation processes.

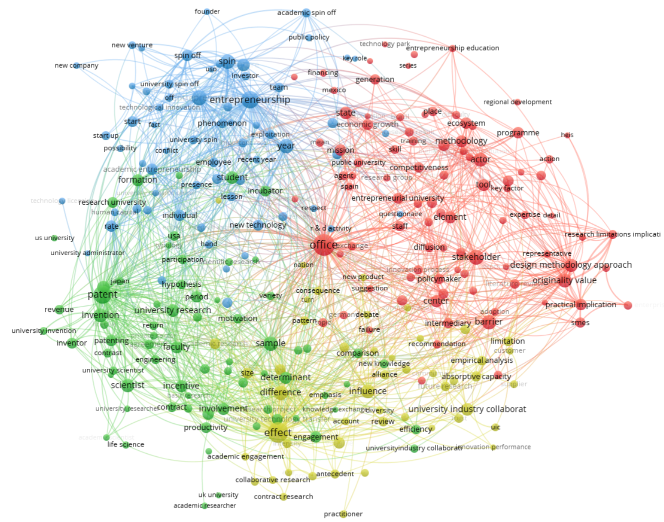

Fig. 1: Keyword co-occurrence network generated in VOSviewer from the Scopus dataset for the period 2000–2024. Node size indicates frequency; edge thickness reflects co-occurrence strength; colors represent thematic clusters.

B. Author Network

The author-level network contains 57 nodes and 432 edges, representing citation relationships among researchers. The structure is not evenly distributed: a limited group of authors concentrates a relevant share of citation links, while most authors occupy less connected positions. This pattern is consistent with previous studies on agricultural and innovation networks, where central actors often operate as knowledge hubs or bridges between research communities [10], [14], [17].

Table VI summarizes the main structural indicators for the author, organization, and country networks.

TABLE VI: Summary of SNA Metrics by Network Type

Network Type	Nodes	Edges	Avg. Degree	Diameter	Clustering Coef.
Authors	57	432	7.579	4	0.278
Organizations	26	40	1.538	4	0.089
Countries	46	541	11.761	3	0.400

The author network has an average degree of 7.579 and a clustering coefficient of 0.278. These values indicate a connected network with low to moderate local cohesion. The diameter of 4 suggests that the longest shortest path between two connected authors requires four steps, allowing citation flows to circulate through a relatively compact structure. However, the moderate clustering coefficient indicates that the network does not form highly closed communities, and that some authors may act as connectors between groups.

Figure 2 presents the author-level citation network, where node size is proportional to degree centrality.

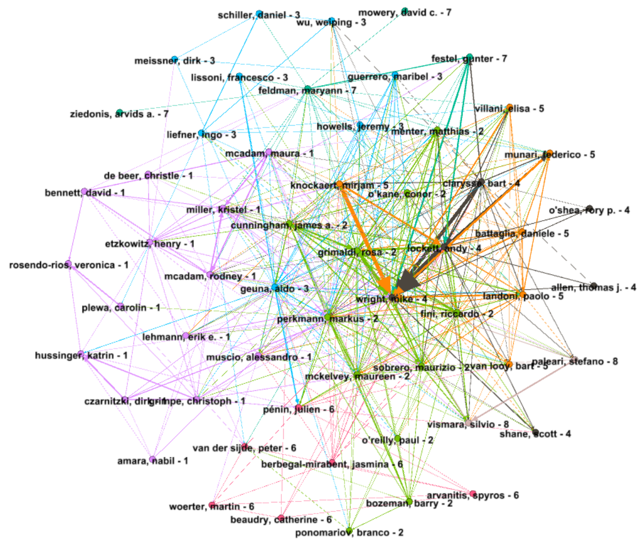

Fig. 2: Citation network by authors. Node size is proportional to degree centrality.

Table VII reports the main central authors identified in the network. Mike Wright occupies the most prominent position, being cited by at least 38 authors and appearing in 16 documents associated with citation relationships. Other relevant actors include Sobrero, Perkmann, McAdam, Lockett, and Muscio, who appear in connected communities within the author-level network.

TABLE VII: Central Authors Identified in the Citation Network

Author	Network evidence	Interpretation
Mike Wright	Cited by at least 38 authors; present in 16 documents	Main knowledge hub in the author network
Sobrero	Central actor in connected communities	Relevant contributor within the citation structure
Perkmann	Central actor in connected communities	Relevant contributor to university–industry transfer literature
McAdam	Central actor in connected communities	Connected actor within the author-level network
Lockett and Muscio	Central actors in connected communities	Relevant authors in the broader citation structure

Figure 3 shows the ego network of Mike Wright. The visualization illustrates his direct and indirect citation connections and supports the interpretation of his role as a central actor in the network.

C. Organization Network

The organization-level network consists of 26 nodes and 40 directed edges. Compared with the author and country networks, this layer presents lower connectivity and greater dispersion. Its average degree is 1.538, and its clustering

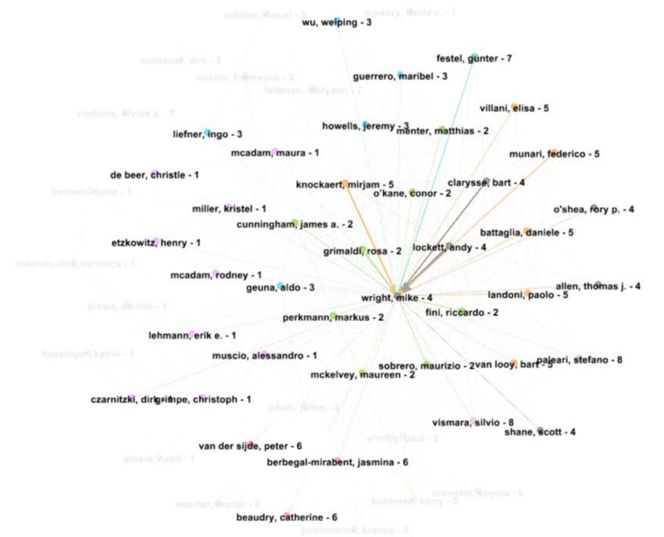

Fig. 3: Ego network of Mike Wright, illustrating direct and indirect citation connections.

coefficient is 0.089, indicating limited local grouping among institutions. This pattern suggests that institutional citation flows are concentrated in a small number of organizations and that dense institutional communities are not strongly developed [9], [18], [24].

Figure 4 displays the organization-level citation network. Table VIII presents the organizations with the highest reported connectivity or link weight.

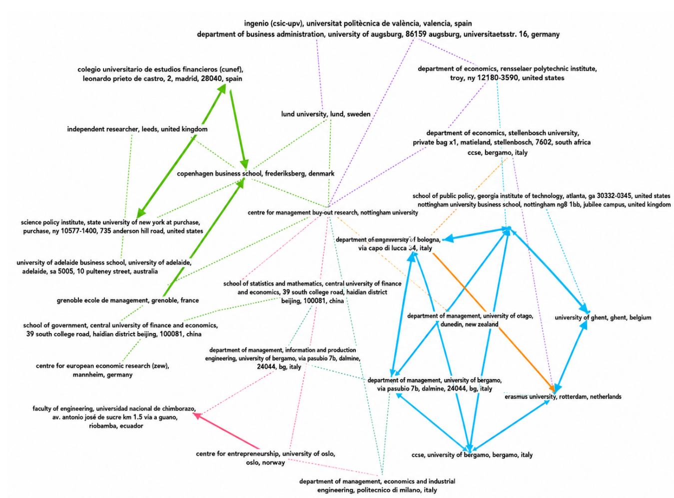

Fig. 4: Citation network by organizations. Arrows indicate citation direction.

The organization network shows that institutional citation relationships are mostly unidirectional and weakly clustered. The low clustering coefficient indicates that the neighbors of

TABLE VIII: Relevant Organizations in the Citation Network

Organization	Reported value	Interpretation
Science Policy Institute, State University of New York at Purchase	Degree = 11	Most connected organization in the institutional network
University of Bologna	Link weight = 12.0	Organization with strong citation relationships
SUNY at Albany	Link weight = 11.0	Organization with strong citation relationships
University of Ghent	Link weight = 7.0	Organization with relevant citation weight

each organization are rarely connected to each other. Therefore, the organizational layer appears more dispersed than the author and country layers, which may restrict the circulation of agroindustrial knowledge across institutions.

D. Country Network

The country-level network contains 46 nodes and 541 edges. It presents the highest average degree among the three layers, with a value of 11.761. The clustering coefficient of 0.400 indicates moderate local cohesion, while the diameter of 3 suggests that citation flows between countries occur through short paths. These results indicate a compact country-level citation structure, with few intermediaries between the most distant connected countries [1], [3].

Figure 5 presents the country-level citation network. Table IX lists the countries with the highest reported influence in the citation structure.

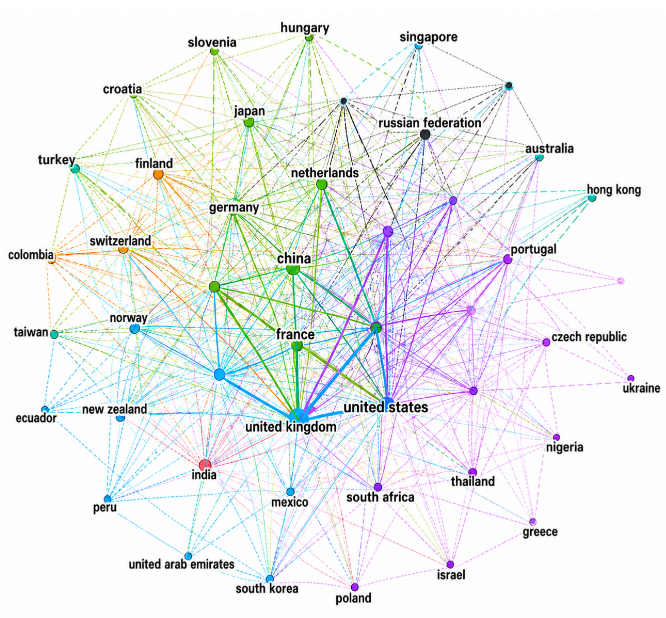

Fig. 5: Citation network by countries. Communities were identified using a modularity-based algorithm.

The country network shows a marked hierarchy in scientific visibility beyond the three focal countries. The United States and the United Kingdom occupy the most influential positions, while Spain also appears as a relevant country in the citation structure. This pattern suggests that agroindustry-related technology transfer research is embedded in broader international knowledge flows and reflects asymmetries between central and peripheral scientific systems.

TABLE IX: Most Influential Countries in the Citation Network

Country	Reported value	Interpretation
United States	Total weight = 17062.0; in-degree = 42	Main knowledge core in the country-level citation network
United Kingdom	Total weight = 14785.0; in-degree = 41	Second most influential country in the citation structure
Spain	Total weight = 3425.0; normalized score = 1.0928	Relevant country with regional influence and strong citation presence

E. Comparative Observations

The comparison of the three citation networks shows that the country network is the most compact layer, the author network presents moderate cohesion, and the organization network is the most dispersed. This pattern is consistent with the network figures and the summary indicators reported in Table VI.

Table X compares density, fragmentation, and cohesion across the three network levels.

TABLE X: Observations on Network Cohesion

Network	Density	Fragmentation	Cohesion Level
Authors	0.135	Low	Medium
Organizations	0.062	Medium	Low
Countries	0.261	Low	High

As reported in Table VI and Table X, the author network shows low to moderate local cohesion, with a clustering coefficient of 0.278 and a density of 0.135. The organization network is the weakest layer, with the lowest clustering coefficient (0.089), the lowest density (0.062), and medium fragmentation. In contrast, the country network is the most compact layer, with the highest average degree, the shortest diameter, and the highest density (0.261) among the three networks.

These comparative results indicate that citation-based knowledge flows are more consolidated at the country level than at the organizational level. This finding is relevant for technology transfer policy because a compact international citation structure does not necessarily imply strong institutional collaboration. The organizational layer therefore remains the main structural weakness, suggesting the need to strengthen inter-institutional linkages, joint research programs, and mechanisms that connect universities, research centers, and agroindustrial actors.

V. Discussion

A. Centrality Patterns and Knowledge Hubs

The results indicate that citation-based knowledge flows in agroindustry-related technology transfer are concentrated around a limited number of connected actors. In the author network, central researchers occupy positions that connect different citation groups, suggesting that knowledge circulation depends partly on authors with brokerage capacity. This pattern is consistent with studies on agricultural innovation networks, where central actors often link weakly connected communities and facilitate the diffusion of technical and scientific information [10], [14], [17].

At the organizational level, the network presents lower connectivity and greater dispersion than the author and country networks. This finding suggests that institutional knowledge flows are less consolidated and depend on a reduced number of organizations with bridging capacity. Such concentration is relevant for technology transfer because institutional fragmentation can limit the movement of research outputs toward firms, producer organizations, and public-sector actors [4]–[6]. In agroindustrial systems, where innovation requires coordination among universities, research centers, firms, and public agencies, weak institutional connectivity may reduce the effectiveness of knowledge transfer mechanisms [7], [11].

The country network shows the most compact structure. Its high average degree and short diameter indicate that citation flows between countries occur through relatively short paths. However, this aggregate cohesion should be interpreted with caution. Countries may appear strongly connected at the international level, while institutions within those countries remain unevenly linked. Therefore, national or international scientific visibility does not necessarily imply strong inter-institutional collaboration [1], [9], [18].

B. Cohesion Differences Across Network Levels

The comparison across network layers reveals three structural patterns. As reported in Table VI and Table X, the author network shows low to moderate local cohesion, with a clustering coefficient of 0.278 and a medium cohesion level. This suggests the presence of specialized research groups connected through central contributors. The organization network is the weakest layer, with the lowest clustering coefficient (0.089), low density (0.062), and medium fragmentation. This indicates limited institutional grouping and weak inter-organizational articulation. The country network is the most compact layer, with the highest average degree, the shortest diameter, and the highest density (0.261) among the three networks.

These differences show that technology transfer cannot be assessed only through aggregate international collaboration. A country-level network may appear cohesive, while the institutional layer may still present weak connections. For agroindustry, this distinction is important because practical technology transfer usually occurs through organizational arrangements, including joint research projects, extension programs, innovation brokers, technical assistance, and university–industry collaboration [7], [8], [11].

C. Interpretation of Community Structure

The thematic and structural clusters indicate that technology transfer research is organized around differentiated areas, including academic entrepreneurship, intellectual property, policy frameworks, absorptive capacity, and university–industry collaboration. These areas are consistent with the literature on knowledge transfer, where commercialization, collaboration, institutional engagement, and innovation capabilities are treated as complementary mechanisms [4]–[6].

The presence of clusters also suggests possible segmentation. When communities are weakly connected, knowledge may circulate within specialized groups but remain less visible across the broader network. This is relevant for agroindustrial systems, where research on patents, entrepreneurship, agricultural innovation, and public policy must interact to support effective technology adoption. Modularity-based community detection is therefore useful for identifying whether the field is organized around integrated knowledge communities or separated thematic blocks [25], [27].

D. Policy Implications for Agroindustry Innovation

The results suggest three policy implications. First, the fragmentation of the organization network indicates the need to strengthen inter-institutional collaboration. This can be addressed through competitive funds that require participation from universities, public research institutes, firms, and producer organizations. Second, actors with high brokerage capacity should be treated as strategic connectors because they can link peripheral institutions with central research communities. Third, regional collaboration should move beyond citation visibility and support practical mechanisms for technology transfer in agroindustrial value chains.

Table XI summarizes the main findings and their policy implications.

For Peru, Colombia, and Mexico, these implications are relevant because agroindustrial competitiveness depends on the articulation of scientific research with productive needs. Collaboration policies should prioritize institutions with low connectivity, support cross-border research agendas, and develop mechanisms that connect academic knowledge with agroindustrial SMEs, cooperatives, and public agencies [2], [13], [20].

E. Limitations

This study has four limitations. First, the use of Scopus restricts the analysis to indexed scientific publications and may exclude regional journals, technical reports, policy documents, theses, and grey literature. This limitation is relevant in Latin America, where part of the knowledge related to agricultural innovation and technology transfer circulates outside mainstream bibliographic databases [21].

TABLE XI: Main Findings and Policy Implications

Finding	Interpretation	Policy implication
Concentration around central authors	Knowledge flows depend on a limited number of influential researchers and citation bridges.	Promote researcher mobility, collaborative publication, and mentoring mechanisms involving peripheral researchers.
Fragmentation of the organization network	Institutional connections are weaker than author-level and country-level citation flows.	Fund joint projects among universities, research centers, firms, and producer organizations.
Compact country-level network	International citation exchange is stronger at the aggregate country level.	Convert regional scientific visibility into concrete inter-institutional technology transfer programs.
Thematic clustering of keywords	Research is organized around entrepreneurship, patents, policy, and collaboration.	Design interdisciplinary programs linking intellectual property, innovation policy, and agroindustrial value-chain upgrading.

Second, citation networks measure academic visibility rather than direct technology adoption. A highly cited author, institution, or country may influence scholarly debate, but this does not necessarily imply effective transfer of technology to firms, producers, or agroindustrial value chains [29]. Third, the analysis is based on an aggregated period from 2000 to 2024; therefore, it does not identify changes in network structure over time. Fourth, the study does not incorporate qualitative evidence from stakeholders, which would be necessary to interpret the practical meaning of the observed network structures.

VI. Conclusion and Future Work

A. Conclusion

This study analyzed citation-based technology transfer networks in agroindustry-related research associated with Peru, Colombia, and Mexico. By applying Social Network Analysis at three levels—authors, organizations, and countries—the study identified differences in centrality, cohesion, and fragmentation across the scientific knowledge structure.

The findings show that the author network is organized around a limited number of influential researchers who occupy central and bridging positions. The organization network presents the highest dispersion, indicating that institutional knowledge flows are less consolidated. The country network is the most compact layer, suggesting stronger international citation exchange. These results show that technology transfer networks cannot be interpreted from a single analytical level. Author, organization, and country networks reveal different dimensions of knowledge circulation.

The main contribution of the study is the use of a multi-level SNA approach to examine agroindustry-related technology transfer in Latin America. This perspective provides evidence for identifying knowledge hubs, institutional gaps, and opportunities for regional collaboration. For policy and management, the results suggest that strengthening institutional linkages is central to improving technology transfer. International citation exchange may be visible at the country level, but practical technology transfer requires stronger collaboration among universities, research centers, firms, producer organizations, and public agencies.

B. Future Work

Future research should expand the empirical and methodological scope of the study. First, broader datasets should be incorporated, including Web of Science, SciELO, Redalyc, patent databases, funded project repositories, policy documents, and industry records. This would reduce database bias and provide a more complete view of scientific and technological knowledge flows.

Second, longitudinal analysis should be conducted by dividing the dataset into time periods. This would make it possible to examine how the networks evolved, whether new actors emerged, and how collaboration patterns changed in response to policy reforms, funding programs, or agroindustrial transformations.

Third, future work should integrate patent, innovation, and project-level data. Patent networks, co-invention records, and technology licensing information would help connect academic citation patterns with more direct indicators of technological application [13], [20]. Fourth, qualitative methods should complement the network analysis. Interviews with researchers, technology transfer offices, firms, producer associations, and public agencies would provide contextual evidence on the mechanisms that explain the observed network structures [3], [18].

Table XII summarizes the recommended future research directions.

TABLE XII: Recommended Future Research Directions

Research direction	Purpose	Expected contribution
Broader bibliographic sources	Include Web of Science, SciELO, Redalyc, and regional repositories.	Reduce database bias and improve regional coverage.
Patent and project data	Incorporate patents, technology licensing records, and funded innovation projects.	Link scientific knowledge flows with technological application.
Longitudinal SNA	Analyze network evolution across different time periods.	Identify changes in central actors, communities, and collaboration patterns.
Qualitative validation	Conduct interviews with researchers, firms, public agencies, and technology transfer offices.	Explain the mechanisms behind observed network structures.
Sector-specific analysis	Examine value chains such as cacao, coffee, fruits, irrigation, and agroindustrial processing.	Connect network gaps with concrete agroindustrial challenges.

Future studies could also examine specific agroindustrial value chains, such as cacao, coffee, fruits, irrigation technologies, and agroindustrial processing. This would move the analysis from general citation structures toward sector-specific technology transfer problems. Such an approach would provide more contextualized evidence on how structural gaps affect innovation, productivity, and sustainability in agroindustrial systems.

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