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Assessing Socio-Economic Centrality Indicators in Urban Research: A Bibliometric and systematic LLM-Assisted Review (2016–2026)

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A b s t r a c t

Socio-economic centrality indicators are widely used to explain the spatial concentration and interaction of economic activities, populations, and services within urban and regional systems. Between 2016 and 2026, rapid methodological diversification and interdisciplinary adoption have generated a fragmented and conceptually heterogeneous body of research. This paper presents a bibliometric and systematic review of socio-economic centrality indicators published between 2016 and 2026, combining classical bibliometric techniques with LLM-assisted semantic synthesis. The combined approach enables the identification of dominant indicator families and their conceptual linkages. Eight socio-economic centrality indicators were identified: (1) accessibility and transport connectivity, (2) mobility and flow-based centrality, (3) economic and commercial activity, (4) amenities and urban attractors, (5) housing prices and investment dynamics, (6) population concentration and demographic indicators, (7) mixed-use development and activity intensity, and (8) innovation and knowledge networks. Results reveal a clear shift from traditional graph-based centrality measures toward multidimensional socio-spatial constructs that integrate these indicators, supported by GIS, big data, and machine learning. Persistent inconsistencies in indicator definition and operationalization are also observed. The study highlights the potential of LLM-assisted reviews to enhance rigor, scalability, and interpretability in urban and socio-economic research.

K e y w o r d s : economic centrality; Bibliometric analysis; Large language models; Urban networks; Spatial analysis; Indicator assessment

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1. Introduction

Urban socio-economic centrality has become a major analytical framework for understanding the spatial organization of cities, particularly regarding the distribution of economic activities, population dynamics, mobility flows, and service accessibility within complex urban systems (Noaime et al., 2025; Y. Zhang et al., 2024). Recent urban research has progressively shifted from traditional graph-based interpretations of centrality toward integrated socio-spatial approaches combining accessibility analysis, mobility patterns, economic interactions, and multi-source urban datasets (Aziz Amen, 2022; Nanni et al., 2020; Y. Zhang et al., 2022). This evolution reflects the growing need to better capture the complexity of urban systems and the interdependence between spatial structure and socio-economic processes.

Despite these advances, the literature on socio-economic centrality remains highly fragmented. A wide diversity of indicators, methodological approaches, and operational definitions has emerged across disciplines, leading to conceptual inconsistencies in the interpretation and measurement of urban centrality (Judijanto et al., 2024; Lan et al., 2022). Studies differ significantly in their use of network-based indicators, accessibility measures, mobility-derived metrics, and economic interaction models, making comparison and synthesis increasingly difficult.

In parallel, Large Language Models (LLMs) are increasingly being explored as tools for LLM-assisted semantic analysis, knowledge extraction, and large-scale literature synthesis within urban studies (Juhász et al., 2022; Kim et al., 2024). Their integration into bibliometric research offers new possibilities for identifying thematic trends, conceptual relationships, and latent structures across diverse scientific domains. (X. Wang, 2006; Zuo et al., 2024). However, despite their growing potential, few studies have combined bibliometric techniques with LLM-assisted semantic analysis to systematically investigate the evolution of socio-economic centrality indicators in urban research.

This study addresses this gap by conducting a bibliometric and systematic LLM-assisted review of socio-economic centrality indicators published between 2016 and 2026. The research aims to: (i) identify the dominant families of socio-economic centrality indicators and their methodological foundations and (ii) examine the thematic and conceptual evolution of urban centrality research. To achieve these objectives, the study combines bibliometric mapping techniques,

including co-citation and keyword co-occurrence analysis, with LLM-assisted semantic synthesis to improve the interpretation of complex and heterogeneous research trends (Judijanto et al., 2024; Lan et al., 2022; X. Wang, 2006).
The growing relevance of urban socio-economic centrality is closely linked to contemporary challenges in sustainable urban development and regional inequality (Tung et al., 2024) (Chen et al., 2021; T. Zhang et al., 2023). Understanding how centrality shapes urban interactions and spatial organization contributes to more informed urban planning and policy-making processes, particularly in rapidly transforming metropolitan regions and polycentric urban systems (Feng et al., 2018; Wei et al., 2020; T. Zhang et al., 2023). Moreover, the integration of artificial intelligence into bibliometric and urban analytical frameworks represents an emerging methodological shift capable of improving research synthesis, interpretability, and knowledge production within urban studies (G. Liu et al., 2019).
By combining bibliometric analysis with LLM-assisted semantic analysis, this study proposes a more coherent and scalable framework for understanding the evolution of socio-economic centrality indicators in urban research. The study contributes both methodologically and conceptually by addressing the fragmentation of existing literature and by highlighting emerging directions at the intersection of urban analytics, network science, and artificial intelligence (Noaime et al., 2025). The overall methodological workflow adopted in this study is illustrated in Figure 1.

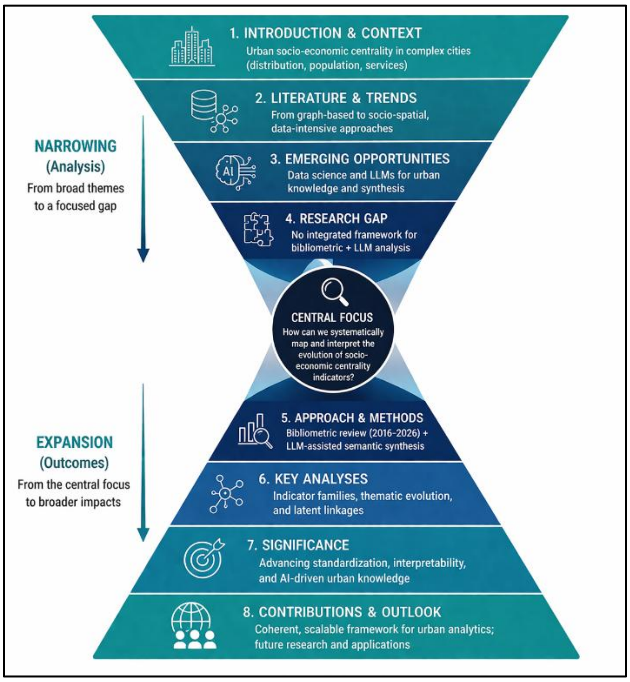

Figure 1. Research Framework Combining Bibliometric Analysis and LLM-Assisted Semantic Analysis.

2. Materials and Methods

2.1 Study design and PRISMA framework

This study adopts a systematic bibliometric review design to investigate the evolution of socio-economic centrality indicators in urban research between 2016 and 2026. The methodological approach is structured in accordance with the PRISMA 2020 guidelines to ensure transparency, reproducibility, and methodological rigor throughout the review process (Page et al., 2021). PRISMA was used to guide the identification, screening, eligibility assessment, and final inclusion of studies, enabling a transparent reporting of the literature selection process and minimizing selection bias in the construction of the final corpus.

2.2 Data sources and search strategy

The bibliometric dataset was constructed using three major academic databases, namely Scopus, Web of Science, and Google Scholar, selected for their extensive coverage of urban studies, spatial analysis, and computational social science literature. A structured search strategy was developed using a combination of keywords related to socio-economic centrality and urban network analysis, including terms such as “socio-economic centrality,” “urban centrality indicators,” “network centrality,” “urban spatial networks,” and “accessibility measures.” Boolean operators were used to refine and combine search strings, ensuring both sensitivity and specificity of the retrieval process. The search was restricted to publications between 2016 and 2026 and limited to peer-reviewed journal articles and review papers written in English.

2.3 Study selection and PRISMA screening process

The study selection process followed the four PRISMA stages of identification, screening, eligibility, and inclusion. In the identification phase, all records retrieved from the selected databases were exported and merged into a reference management system Zotero, where duplicate entries were systematically removed. During the screening phase, titles and abstracts were examined to exclude studies that were not relevant to urban socio-economic centrality, including those focused purely on theoretical network science or unrelated spatial systems. In the eligibility phase, full-text articles were assessed in detail to ensure that they explicitly addressed socio-economic or spatial centrality indicators within urban or regional contexts. Studies that did not provide measurable, conceptual, or methodological engagement with centrality indicators were excluded. Finally, the inclusion phase resulted in a refined dataset of studies that formed the basis for both bibliometric and LLM-assisted analysis (Theocharopoulos et al., 2025). The entire selection process is reported following PRISMA standards, and a flow diagram was constructed to document the number of records at each stage along with exclusion reasons.

2.4 Inclusion and exclusion criteria

The eligibility of studies was determined using predefined inclusion and exclusion criteria. Studies were included if they were published between 2016 and 2026, were peer-reviewed journal articles or review papers, and explicitly focused on socio-economic or spatial centrality within urban or regional systems. Eligible studies were also required to employ or discuss centrality indicators derived from network analysis, GIS-based methods, accessibility modelling, or mobility and interaction data. Studies were excluded if they were not related to urban contexts, did not address measurable or conceptual centrality indicators, or were classified as conference abstracts, editorials, or non-peer-reviewed publications. Non-English publications were also excluded to maintain consistency in textual analysis and LLM processing (Kashyap, 2025).

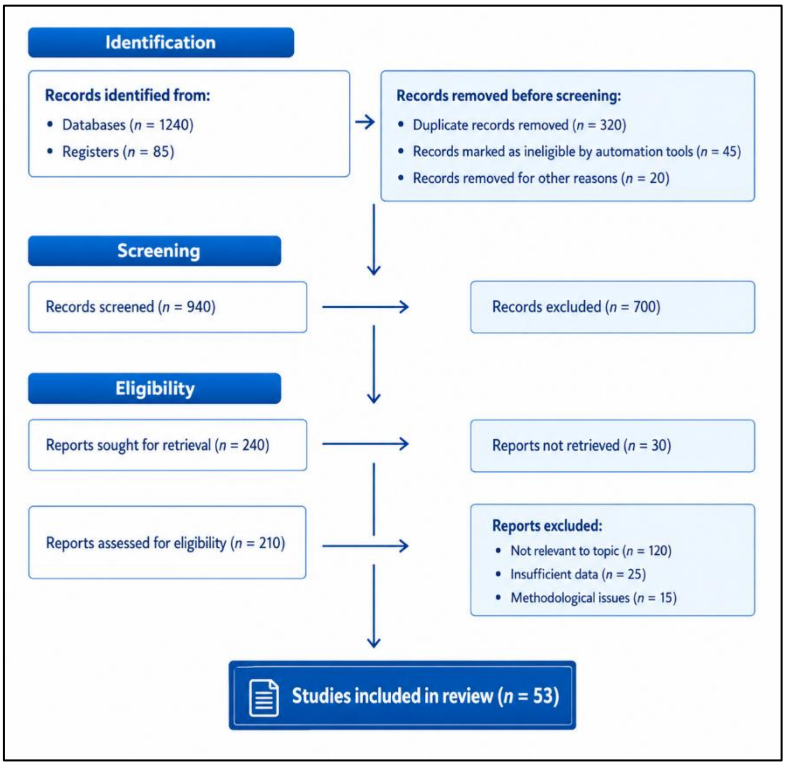

Figure 2. PRISMA 2020 Flow Diagram of the Literature Selection Process.

2.5 Bibliometric Analysis

The bibliometric analysis was conducted to map the intellectual structure and thematic evolution of socio-economic centrality research. Co-citation analysis was used to identify influential authors, journals, and foundational works that have shaped the field. Keyword co-occurrence analysis was employed to detect dominant research themes and conceptual groupings, while thematic evolution analysis was used to examine how research priorities and methodological approaches have shifted over the selected time period. Network mapping techniques were applied to visualize relationships among authors, keywords, and publications, allowing for the identification of major clusters such as accessibility-based centrality, mobility-driven networks, and GIS-integrated spatial interaction models.

2.6 LLM-Assisted Semantic Analysis

To complement traditional bibliometric techniques, this study integrates large language model (LLM)-assisted semantic analysis to enhance the conceptual interpretation and thematic synthesis of the reviewed literature (Cao et al., 2025). Specifically, Claude 3.5 Sonnet (Anthropic, 2024), accessed via the Anthropic API, was selected as the primary LLM for semantic processing, owing to its demonstrated strengths in scientific text comprehension, structured information extraction, and multi-document reasoning across heterogeneous corpora.

Abstracts and relevant textual excerpts from the final included studies were systematically processed through a standardized prompting pipeline. Each input was structured to instruct the model to perform three distinct analytical tasks: (i) extraction of methodological descriptions, including the types of centrality indicators employed and the analytical frameworks applied; (ii) identification of indicator definitions and their operational contexts; and (iii) detection of conceptual relationships between centrality constructs across disciplinary boundaries. All prompts were designed following a zero-shot instruction format with explicit output structure specifications, ensuring consistency and comparability of responses across the entire corpus.

A Retrieval-Augmented Generation (RAG) architecture was implemented to mitigate the risk of hallucinated or context-free interpretations. Under this framework, each LLM query was conditioned on the verbatim text of the corresponding abstract or passage retrieved from the corpus, rather than relying on the model's parametric knowledge alone. Document chunking was applied where full-text content exceeded the model's context window, with overlapping segments used to preserve semantic continuity across chunk boundaries. This design ensured that all generated interpretations remained directly traceable to specific source texts.

The LLM was further employed to identify latent semantic structures that are not readily detectable through conventional keyword-based bibliometric approaches; particularly in cases where different disciplines employ inconsistent or discipline-specific terminology to describe conceptually equivalent centrality constructs (Theocharopoulos et al., 2025). For instance, terms such as "accessibility index," "network centrality," "spatial interaction potential," and "proximity measure" were semantically reconciled through model-assisted concept mapping, enabling cross-disciplinary thematic aggregation that would otherwise be obscured by surface-level lexical variation.

To ensure reproducibility and auditability, all prompts used in the analysis were documented in a structured prompt log, recording the exact instruction text, model version, temperature setting (set to 0 for deterministic outputs), and the corresponding source document identifier for each query. Model outputs were stored in a structured JSON format linking each LLM-assisted semantic analysis to its source abstract, enabling full traceability of the analytical chain.

2.7 Hybrid Integration and Validation Strategy

The final analytical stage involved an integrated interpretation framework in which bibliometric outputs were systematically triangulated with LLM-derived semantic insights to produce a multi-layered understanding of the research landscape. Quantitative results from co-citation network analysis and keyword co-occurrence mapping were paired with qualitative thematic interpretations generated through the LLM pipeline, allowing structural patterns in the literature to be enriched with contextual and conceptual meaning.

To ensure the reliability and validity of LLM-generated outputs, a multi-step validation protocol was applied. First, a human review of a randomly selected subset of LLM outputs corresponding to approximately 20% of the total processed abstracts was conducted by the research team, who assessed the accuracy, completeness, and faithfulness of extracted concepts against the original source texts. Discrepancies were recorded, reviewed, and used to iteratively refine prompt formulations where systematic extraction errors were identified. Second, inter-rater consistency between LLM-extracted themes and bibliometrically identified keyword clusters was assessed qualitatively, with strong convergence across both methods treated as a positive validity indicator and divergences flagged for closer manual examination. Third, all conceptual claims derived from LLM-assisted synthesis were cross-referenced against the original articles prior to inclusion in the findings, ensuring that no interpretation was reported without grounding in verifiable source content.

This hybrid methodology improves the overall robustness of the review by combining the scalability and pattern-detection capacity of computational bibliometric methods with the contextual reasoning capabilities of large language models, while maintaining the interpretive accountability required by systematic review standards. The full prompt documentation, output logs, and validation records are retained and available upon request to support transparency and replication of the methodological workflow represented in Figure 3. The overall LLM-based analytical pipeline adopted in this study is illustrated in Figure 3. The workflow is organized into six sequential stages, each representing a specific phase of data processing, semantic interpretation and validation.

Stage 1 Input: The screened corpus feeds into abstract extraction, then documents are chunked into overlapping segments to preserve semantic continuity across long texts.

Stage 2 Retrieval: Chunks are embedded into a vector index. For each query, the RAG system retrieves the top-k most relevant chunks and assembles them into a grounded prompt; this is what prevents hallucination.

Stage 3 Processing: Claude 3.5 Sonnet (temperature = 0 for determinism) receives the assembled prompt and generates structured responses. The zero-shot instruction format ensures comparable outputs across all articles.

Stage 4 Extraction: Three parallel extraction tasks run simultaneously, methodological frameworks, indicator definitions, and cross-discipline concept mapping. All outputs are logged to JSON with prompt text, model version, and source ID for full traceability.

Stage 5 Validation: Three parallel checks run: a 20% human-reviewed random sample against source texts, an inter-rater consistency checks comparing LLM themes to bibliometric clusters, and a full source cross-reference for every claim. The dashed feedback arrow on the left shows that errors found here loop back to refine the prompts iteratively.

Stage 6 Integration: Validated semantic outputs are triangulated with bibliometric co-citation and keyword data to produce the final thematic synthesis.

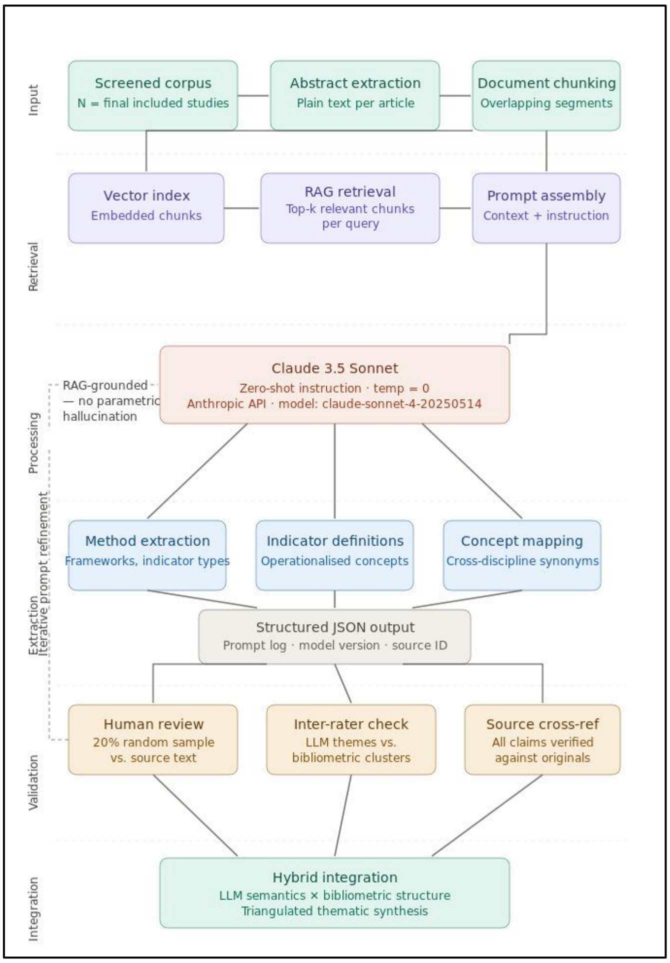

Figure 3. LLM-Based Analytical Pipeline.

3. Results Overview of Centrality Assessment Studies

3.1 Geographical Distribution of Studies

The spatial distribution of the reviewed studies reveals a strong geographical imbalance. Asian contexts, particularly China, dominate the literature, accounting for approximately 42% of the total sample. This is followed by global or multi-country studies (18%), which typically adopt comparative or conceptual frameworks. European contexts (including Italy, the Netherlands, Poland, France, and others) represent around 15%, while South Korea contributes approximately 9% of the studies. The remaining 16% is distributed across diverse regions such as Iran, India, the MENA region, the United States, Brazil, and Colombia.

This distribution indicates a significant regional concentration of empirical research in East Asia, particularly in rapidly urbanizing and polycentric systems. Conversely, regions such as Africa and parts of the Middle East remain underrepresented, highlighting a gap in geographically diverse empirical validation. The geographical distribution of the reviewed studies reveals a strong concentration of research in East Asia, particularly China (Figure 4).

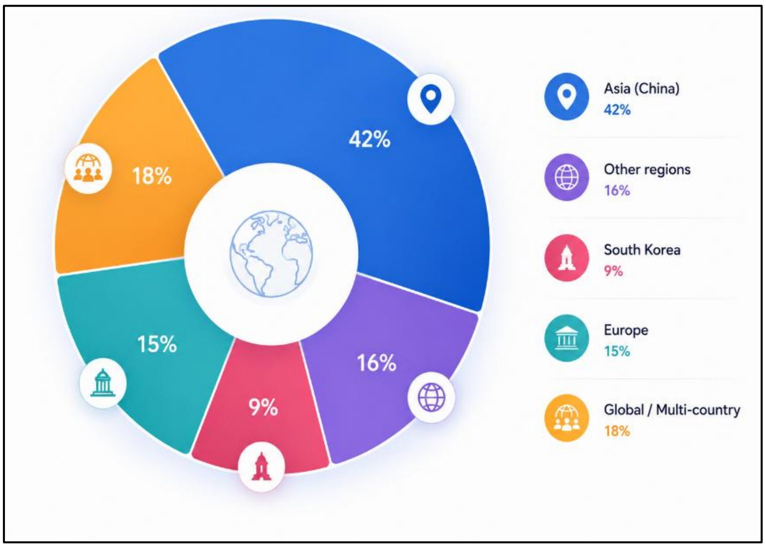

Figure 4. Geographical Distribution of Reviewed Studies (2016–2026).

3.2 Methodological Distribution

The methodological analysis demonstrates a clear dominance of quantitative and network-oriented approaches. Network analysis techniques, including social network analysis (SNA), graph theory, and centrality metrics, constitute the most frequently used approach, representing approximately 38% of the studies.
Regression-based models, including spatial econometrics, and geographically weighted regression (GWR), account for about 23%, often used to link centrality with economic or spatial outcomes.
Composite and multi-criteria methods (such as PCA, entropy-weighted TOPSIS, clustering, and index construction) represent approximately 18%, reflecting a growing interest in multidimensional centrality assessment.
Mixed-methods approaches, combining network analysis with econometric or GIS-based techniques, account for roughly 14%, while qualitative and conceptual approaches remain limited at around 7%.
This distribution confirms that centrality research is predominantly quantitative and data-driven, with increasing integration of hybrid methodologies. Quantitative and network-oriented approaches dominate the methodological landscape of socio-economic centrality research **(Figure 5).**

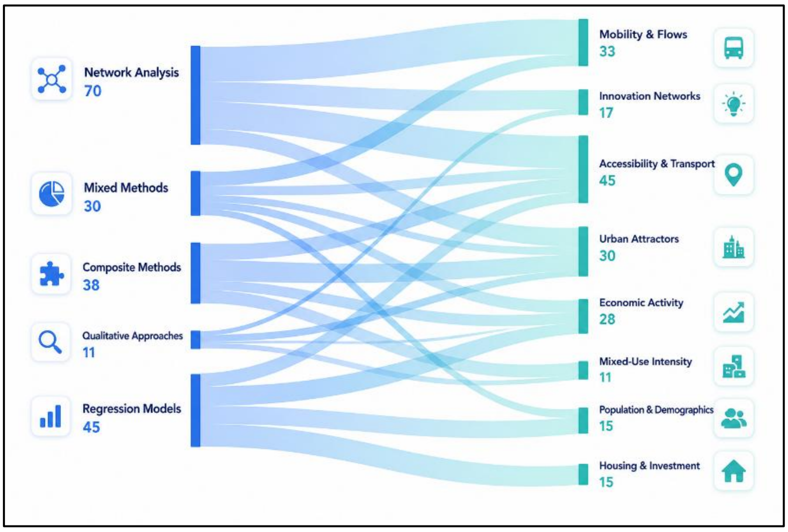

Figure 5. Methodological Distribution of Urban Centrality Studies.

The conceptual trajectory of centrality research demonstrates a shift from graph-theoretic approaches toward multidimensional and sustainability-oriented frameworks (Figure 6).

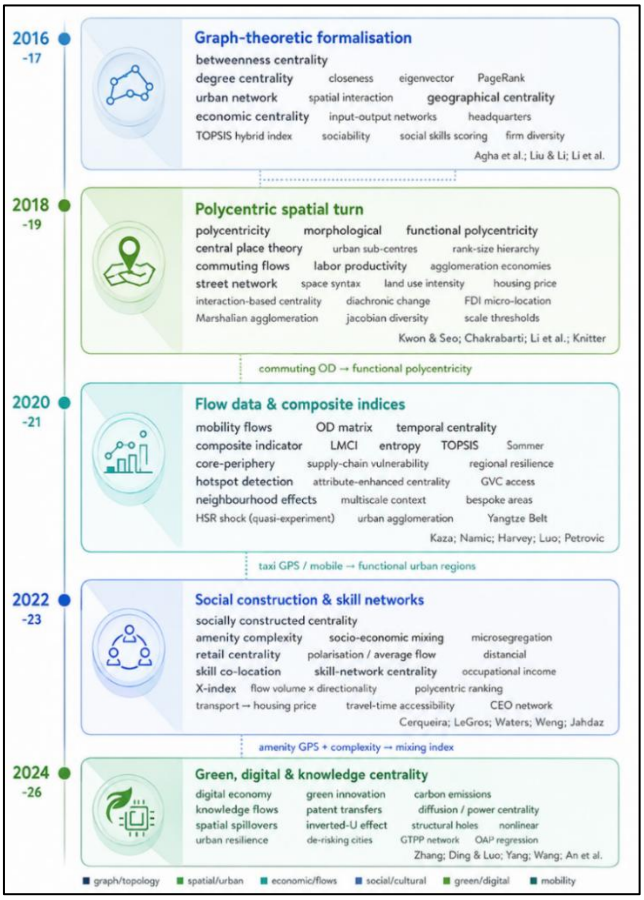

Figure 6. Conceptual Evolution of Centrality Research (2016–2026).

Centrality research follows a clear conceptual trajectory over the past decade. Starting from formal graph-theoretic metrics (betweenness, degree, closeness, eigenvector), the field underwent a polycentric spatial turn in 2018–2019, substituting commuting flows and space syntax for abstract topology. In 2020–2021, dissatisfaction with single metrics generated composite indices (LMCI, entropy-TOPSIS, Sommev) and the integration of big mobility data (OD matrices, GPS, mobile traces), introducing previously absent temporal and dynamic dimensions.
A socio-cultural inflection sharpened in 2022–2023: centrality became conceived as socially constructed through daily mobility practices, retail behavior, and amenity complexity; skill co-location networks simultaneously linked centrality to occupational income, bridging the graph-theoretic and economic traditions.
The most recent cluster (2024–2026) converges on sustainability outcomes carbon emissions, green innovation, and urban resilience with the digital economy functioning as a polycentric amplifier.
Two structural tensions run throughout the corpus. First, the structure–agency opposition: early studies treat centrality as a topological fact, whereas later studies conceptualize it as a relational product of practices, yet few explicitly bridge both ontologies. Second, an enduring circularity central places attract firms because they are productive, and are productive because firms locate there which only quasi-experimental designs (HSR shocks, GVC exposure) begin to break. "Polycentricity" and "flows" remain the two master signifiers tying the entire literature together.

4. Results

The reviewed literature was classified into eight major categories of socio-economic centrality indicators, as presented in Table 1

Table 1. Classification of Reviewed Articles by Urban Centrality Indicator Category.

Centrality Category	Articles (APA in-text citations)
1. Accessibility & Transport Connectivity	(Bowater & Stefanakis, 2023; Mussone et al., 2024; Nielsen et al., 2021; Weiss et al., 2018)
2. Mobility & Flow-Based Centrality	(Li, Qian, & Liu, 2017); (Nanni et al., 2020); (Shen et al., 2024); (X. Wang et al., 2023); (Y. Wang & Niu, 2023); (Pan et al., 2024)
3. Economic & Commercial Activity	(An et al., 2024; Ayadi et al., 2024; Dadashpoor & Saeidi Shirvan, 2019; Y. Ding & Luo, 2024; Dzhurka, 2024; Grechyna, 2020; Kwon & Seo, 2018; Lee & Seo, 2023; Petrović et al., 2022; Waters & Shutters, 2022)
4. Amenities & Urban Attractors	(Bowater & Stefanakis, 2023); (He et al., 2025); (Juhász et al., 2023); (Lee & Seo, 2021); (Lee & Seo, 2023); (Li, Zhou, & Wen, 2019)
5. Housing Prices & Investment Dynamics	(Chakrabarti et al., 2022); (Luo et al., 2020); (Pan et al., 2024)
6. Population Concentration & Demographic Indicators	(Shen et al., 2024)(D. Li et al., 2025; Lu et al., 2024; Luo et al., 2020; Salon & Salon, 2025; Shen et al., 2024)
7. Mixed-Use Development & Activity Intensity	(Ayadi et al., 2024; P. Ding et al., 2024; J. He et al., 2024; Juhász et al., 2022; Y. Li, Zhao, et al., 2024; Nanni et al., 2020; Pan et al., 2024)
8. Innovation & Knowledge Networks	(Ayadi et al., 2024; Lebrun, 2024; Pokharel et al., 2023; Romano et al., 2017; S. Wang et al., 2023; Waters & Shutters, 2022; Y. Zhang et al., 2024)

4.1 Accessibility and Transport Connectivity as Indicators of Centrality

Accessibility and transport system connectivity constitute fundamental dimensions of urban and regional centrality, as they reflect the degree of integration of a place within spatial and infrastructural networks. This integration directly conditions its capacity to structure flows, attract activities, and support economic development.
At the intra-urban scale, street networks play an essential role in structuring local centralities. Highly connected intersections and corridors concentrate movement flows and function as urban attraction poles, thereby reinforcing the internal spatial hierarchy of cities. This network organization contributes to the concentration of activities in the most accessible areas.
At the interurban scale, transport infrastructure ensures the integration of cities into broader regional systems. Efficient systems improve connectivity between urban centers and strengthen territorial spatial cohesion (Baek & Joo, 2022). The development of high-speed rail lines illustrates this structuring role by fostering economic interactions and reducing functional distances between cities (Meng et al., 2022).
At the regional scale, transport networks structure territorial centrality by generating corridors and strategic nodes that organize exchanges and spatial hierarchies. These corridors become major development axes, fostering the emergence of secondary centers and the reconfiguration of territorial dynamics (Pokharel et al., 2023).
Accessibility is also a major determinant of economic attractiveness. Well-served areas concentrate more activities and exhibit higher land values, reflecting a positive relationship between transport accessibility and real estate prices. At the global scale, comparative analyses also reveal significant inequalities in connectivity between urban regions (Weiss et al., 2018).

4.2 Mobility and Flow-Based Centrality

Mobility-based approaches complement accessibility indicators by focusing on actual flows of people, goods, and information within urban systems. They reveal functional interactions and the dynamic organization of urban networks across different scales.

At the urban scale, home-to-work flows constitute a central indicator, as they structure daily movements between residential areas and employment centers. Their analysis helps identify labor market hubs as well as center–periphery relations within metropolitan regions. Empirical studies show that employment centers play a structuring role in the organization of regional labor markets (Kaza & Nesse, 2021), while combining mobility and activity data facilitates the identification of emerging metropolitan centers (Lee & Seo, 2021).

At the scale of city systems, mobility flows also reveal hierarchical structures within interurban networks. Gravity-model-based analyses show a concentration of interactions around a limited number of dominant poles, producing center–periphery systems at national or regional scales (Q. Li et al., 2026). Moreover, network analysis of economic interactions enables the identification of functional clusters and the ranking of cities according to their relative centrality (Y. Li, Zhao, et al., 2024)

Recent advances in urban data science increasingly rely on large-scale datasets, particularly mobile phone traces and geolocated services. These datasets provide fine-grained detail to map population movements and classify cities into central hubs, secondary centers, and peripheral areas (Shen et al., 2024). Origin–destination networks further allow the analysis of the temporal dimension of centrality and the detection of spatio-temporal variations in urban hotspots (Nanni et al., 2020).

4.3 Economic and Commercial Activity

Economic and commercial dynamics constitute a central dimension in the analysis of urban centrality, as they reflect the spatial organization of production, exchange, and value creation within territorial systems.

At the microeconomic scale (firms), centrality is observed through organizational structures and inter-firm networks. The spatial distribution of multinational corporations, as well as their investment relations, highlights the structuring of economic power and the formation of urban hierarchies (Hussain et al., 2019). Furthermore, the location of headquarters and the intensity of interurban cooperation confirm the role of certain cities as strategic decision-making centers (L. Liu & Li, 2017).

At the mesoeconomic scale (sectors and production systems), centrality is based on industrial organization and interdependencies between activities. Input–output analyses show that certain sectors occupy structuring positions within regional production systems by connecting different industrial chains and contributing to system resilience (Harvey & O'Neale, 2019). In addition, the spatial concentration of specialized activities in the form of localized production systems, combined with high accessibility to transport infrastructure, reinforces specialization and the economic importance of certain urban spaces (Y. Ding & Luo, 2024).

At the macroeconomic scale (cities and urban systems), centrality is expressed through economic flows, particularly trade, financial, and investment flows. Cities strongly integrated into global economic networks exhibit a high level of insertion into international markets and occupy strategic positions within urban systems (Grechyna, 2020). Imbalances in intercity exchanges also contribute to the structuring of polycentric configurations characterized by differentiated and complementary roles (Y. Li, Zhao, et al., 2024).

At the global scale, economic centrality results from agglomeration processes. The spatial concentration of firms, services, and labor generates positive externalities such as productivity gains, innovation dynamics, and territorial attractiveness. These mechanisms contribute to the consolidation of dominant economic centers within international urban hierarchies (Nielsen et al., 2021; Przybyła et al., 2024).

4.4 Amenities and Urban Attractors

Urban attractors are elements that draw people, activities, and investments, thereby shaping mobility patterns, land use, and urban dynamics. They may be physical, functional, or symbolic and include transport hubs, cultural institutions, public spaces, and mixed-use developments.

In urban analysis, attractors correspond to places that generate or concentrate movement due to their functional importance. In street network studies, they often correspond to highly connected intersections or corridors where pedestrian and vehicular flows accumulate (D'Alessandro, 2016).

Points of Interest (POI) databases provide a detailed representation of urban attractors by mapping the distribution of activities such as retail, services, and leisure. These datasets allow the identification of functional urban centers and activity clusters (Lee & Seo, 2023). When combined with street network analysis, they reveal strong relationships between spatial centrality and the concentration of urban services (Q. Li et al., 2019)

Recent studies integrate POI data with mobility flows to create composite centrality indicators, such as the X-index, which captures both activity concentration and movement intensity (S. Wang et al., 2023).

4.5 Housing Prices and Investment Dynamics

Real estate prices and investment flows can also serve as indicators of urban centrality, as they reflect the economic attractiveness of specific locations. Central areas generally exhibit higher land values due to their accessibility, concentration of services, and economic opportunities.

Real estate prices are often used as indirect measures of centrality. Highly accessible areas tend to experience greater demand and higher property values, reflecting their attractiveness for residential and commercial development (Chakrabarti et al., 2022).

Investment flows constitute another indicator. Cities occupying central positions within economic networks typically attract larger volumes of capital and investment, thereby reinforcing their strategic role within global systems (Grechyna, 2020). The concentration of multinational corporations and financial networks can also strengthen the status of major metropolises as global command centers (Hussain et al., 2019).

4.6 Population Concentration and Demographic Indicators

Population indicators are widely used to identify urban centrality, as demographic concentration and distribution reflect the presence of urban poles and functional zones. High density and significant population agglomeration generally indicate areas of concentrated services, activities, and interactions (Pan et al., 2024).

Population density also allows the analysis of the morphological and functional organization of urban spaces, particularly when combined with commuting flows to distinguish forms of polycentricism (Kwon & Seo, 2018) and to study relationships between spatial and socio-economic structures (Mao et al., 2018).

In economic and regional analyses, demographic data are used to identify employment centers and urban hierarchies by integrating mobility flows and other spatial and economic variables (Kaza & Nesse, 2021; Y. Li, Zhuang, et al., 2024; Lu et al., 2024; Przybyła et al., 2024). Recent approaches also exploit big data, including mobile phone data, to classify urban spaces according to their activity and mobility dynamics (Shen et al., 2024). Overall, population remains a key indicator of urban centrality.

4.7 Mixed-Use Development and Activity Intensity

Mixed-use development and activity density define urban centrality by concentrating diverse commercial, residential, and institutional functions. Research confirms that amenity and functional diversity attract varied users and boost socio-economic interaction (Juhász et al., 2023; Lee & Seo, 2021). Central streets and metropolitan agglomerations thrive on this functional mix, which fosters dynamic, multi-center regions (Li et al., 2019; Pan et al., 2024). Furthermore, high activity density—driven by strategic land-use patterns and local interaction networks—enhances urban vitality and accessibility at both the neighborhood and city scales (Yan et al., 2021; Vámos et al., 2024; Sapena et al., 2020; Xia et al., 2020).

4.8 Innovation and Knowledge Networks

Innovation systems and knowledge networks provide another perspective for understanding urban centrality. In this framework, central cities are those capable of producing, attracting, and diffusing knowledge and technological innovation within interconnected networks.

A key indicator concerns knowledge production and flows. Cities with strong research institutions, high patent activity, and a skilled workforce accumulate substantial knowledge stocks. However, centrality also depends on the intensity of collaboration and information exchange with other cities (Y. Zhang et al., 2024). Thus, cities actively participating in knowledge diffusion generally occupy central positions in innovation networks.

Digital economy networks represent another dimension of centrality. Cities with strong digital connectivity and technological collaboration often act as innovation hubs. However, the relationship between network centrality and innovation is not always linear, as intermediate levels of connectivity may produce better outcomes than overly dense networks (Y. Zhang et al., 2024).

Industrial production networks also reveal economic centrality. Input–output analyses show that certain industries act as nodes connecting multiple sectors within regional production systems (Harvey & O'Neale, 2019). Cities hosting these industries often play a coordinating role in regional economies.

Innovation networks in specialized sectors, such as green technologies, also illustrate hierarchical structures in knowledge diffusion. A limited number of dominant cities typically act as central nodes ensuring the spread of innovation at regional scale (K. Wang et al., 2022).

Finally, the mobility of skilled labor and the circulation of knowledge between cities strengthen innovation networks and contribute to the formation of central and intermediate cities within regional systems (Yang et al., 2024).

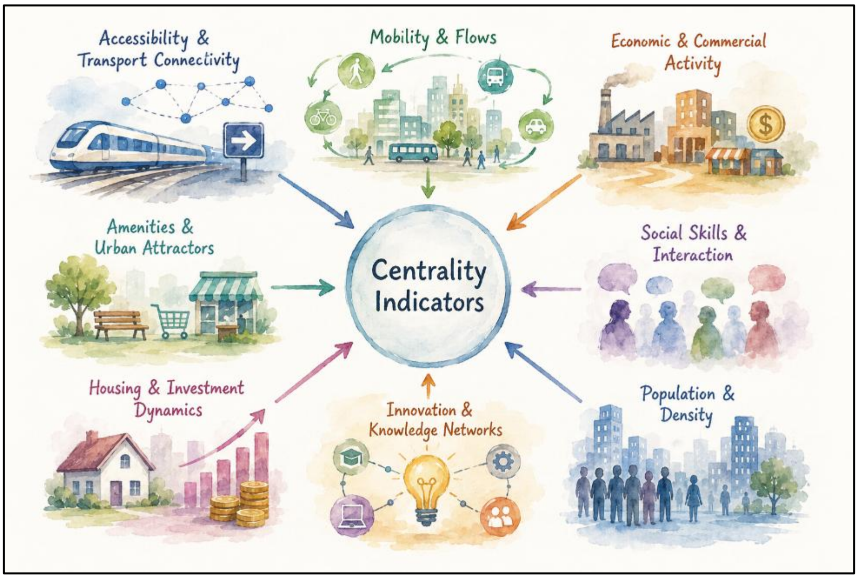

Figure 7. Thematic Clusters of the Centrality Research (2016–2026).

5. Discussion

A synthesis of the results suggests that urban centrality should not be interpreted as the sum of separate indicators, but rather as an emergent property of interacting systems. the reviewed literature indicates that centrality is produced through the alignment or misalignment of multiple dimensions operating simultaneously. When accessibility, economic intensity, and mobility flows converge in the same locations, strong and stable centers emerge. However, when these dimensions are spatially or functionally disconnected, fragmented or "latent" centralities appear: places with high potential but limited actual influence in practice.

This misalignment is a critical but often overlooked mechanism explaining why some well-located areas consistently fail to develop into active urban centers. It also explains why single-indicator assessments so frequently produce misleading conclusions. A location may score highly on transport connectivity while remaining economically inert; it may attract residential population without generating the flows and exchanges that define functional centrality. The clearest empirical demonstration of this dynamic comes from China's Pearl River Delta, where several planned satellite cities including Nansha and Huadu were constructed with dense road networks and metro access yet remained commercially inactive for over a decade. This mismatch resulted from housing investment advancing significantly faster than employment relocation and retail development, producing areas of high morphological centrality without the functional dimension that animates it (Shen et al., 2024). Pan et al. (2024) quantified this gap with particular precision, using origin-destination matrices across Beijing's metro network to show that stations in outer districts ranked in the top quartile for topological centrality yet fell in the bottom quartile for actual boarding flows. The divergence was explained almost entirely by the absence of mixed-use zoning within 800 meters of station entrances. These cases carry a direct methodological implication for researchers and planners alike: composite centrality assessments must systematically cross-validate structural indicators against flow-based indicators, because a high score on one dimension in the absence of the other is a diagnostic signal of latent rather than active centrality.

The temporal instability of centrality constitutes a second dimension that the literature consistently underestimates. Centrality is not a fixed property of a place but a condition that fluctuates depending on daily rhythms, economic cycles, and evolving mobility patterns. Treating a single-period measurement as representative of a location's centrality produces a systematically distorted picture, yet this remains the dominant practice across the reviewed studies.

Nanni et al. (2020) made this problem concrete through an analysis of Milan's mobility network across a full week of GPS and transit data. Their findings were striking: the centrality ranking of the central business district fell by nearly 30 percent relative to mixed-use neighborhoods during weekend afternoons, and cultural districts that ranked outside the top ten on weekday mornings entered the top three by Saturday evening. Infrastructure investment decisions made solely on the basis of weekday commuter flows would have systematically undervalued the functional importance of districts whose economic contribution is concentrated in leisure, tourism, and evening economies. A structurally similar finding emerged from Juhász et al.'s (2022) longitudinal study of Budapest. Tracking centrality patterns between 2019 and 2022, they found that the transition to hybrid working reduced the measured centrality of the traditional CBD by approximately 18 percent, while residential neighborhoods with high amenity density rose correspondingly in relative importance. Crucially, this shift was not anticipated by any of the static land-use models in use at the time, and only became visible through repeated temporal measurement at fine spatial resolution (Juhász et al., 2022). Together, these cases establish that temporal granularity is not a methodological refinement to be added where data permits it is a substantive requirement for accurate centrality assessment, without which planning decisions risk being calibrated to a past or partial reality.

A third mechanism that the results consistently point toward, but rarely surface explicitly, concerns threshold effects and tipping points in the formation of centrality. The accumulation of activities, flows, or investments does not produce proportional or linear outcomes. Instead, centrality tends to emerge abruptly once a critical mass of co-located functions is reached, and to decline rapidly when that mass is disrupted. Below the threshold, investment produces little visible return; above it, growth becomes self-reinforcing. This non-linearity has significant consequences for how urban interventions are designed and evaluated.

The expansion of China's high-speed rail network provides the most thoroughly documented evidence of this dynamic at the inter-city scale. Luo et al. (2020) analyzed land value, enterprise registration, and commuting data across 87 Chinese cities before and after HSR connection, finding that centrality gains were highly non-linear. Cities that achieved a travel-time reduction to the nearest metropolis of below 90 minutes experienced investment inflows three to four times larger than cities that achieved reductions of between 90 and 150 minutes a threshold effect rather than a dose-response relationship. Cities just above the threshold showed negligible gains despite substantial infrastructure expenditure, confirming that accessibility improvements that fall short of a functional threshold generate almost no centrality return. At the intra-urban scale, Lee and Seo (2021) documented a comparable tipping point within Seoul's Gangnam district. The cumulative arrival of flagship retail anchors between 2010 and 2016 crossed a density threshold that triggered a self-reinforcing relocation of complementary services, converting a previously secondary commercial strip into the highest-rent retail corridor in South Korea within six years. Once the threshold was crossed, the transition accelerated and showed no sign of reversal within the study period. The planning implication of both cases is precise: incremental investment that remains below a functional threshold is likely to be absorbed without producing measurable centrality gains, while targeted investment explicitly designed to reach threshold conditions can unlock disproportionate and durable returns.

6. Conclusions

The present study set out to systematically examine the evolution, structure, and conceptual foundations of socio-economic centrality indicators in urban research between 2016 and 2026, while assessing the added value of integrating large language model (LLM)-assisted semantic analysis with classical bibliometric techniques. By addressing the fragmentation and heterogeneity of existing approaches, the research aimed to provide a more coherent understanding of how centrality is defined, measured, and operationalized across disciplines.

The findings reveal a clear transition from traditional graph-based centrality metrics toward multidimensional and hybrid constructs that integrate accessibility, mobility flows, economic interactions, and increasingly, data-intensive methodologies such as GIS, big data analytics, and machine learning. The results further highlight a strong dominance of quantitative, network-oriented approaches, alongside a growing use of composite and mixed-method frameworks. At the empirical level, centrality emerges as a multi-scalar and relational phenomenon shaped by the interaction of transport connectivity, mobility dynamics, economic activity, demographic concentration, and urban attractors. However, persistent inconsistencies in definitions and measurement frameworks confirm the disconnected nature of the field, limiting comparability across studies.

These results suggest that socio-economic centrality should be understood not as a static or singular metric, but as a dynamic and emergent property resulting from the alignment of multiple spatial and functional dimensions. The study underscores the importance of temporal variability, intermediary structures, and non-linear threshold effects in shaping centrality patterns, thereby challenging conventional static and purely spatial interpretations. In doing so, it reframes centrality as a process-driven and network-dependent phenomenon, where relational positioning and functional integration are as critical as spatial concentration.

This research contributes methodologically, conceptually, and empirically to the study of urban socio-economic centrality.

Empirically, it provides a comprehensive mapping of global research trends, identifying dominant themes, methodological biases, and significant geographical imbalances, particularly the underrepresentation of regions such as Africa and parts of the Middle East.

Nevertheless, the study is not without limitations. The reliance on selected academic databases and English-language publications may have excluded relevant contributions from other sources and linguistic contexts. Additionally, while LLM-assisted analysis enhances synthesis, it remains dependent on the quality and representativeness of the input corpus, and may introduce interpretative biases despite the use of retrieval-augmented strategies. The bibliometric approach itself also prioritizes structural patterns over in-depth case-specific insights.

From a practical perspective, the findings highlight the need for greater standardization and harmonization of centrality indicators to support their application in urban planning and policy-making. Planners and decision-makers should adopt multidimensional and context-sensitive frameworks that account for the dynamic and relational nature of centrality, particularly when addressing issues of spatial inequality, infrastructure investment, and polycentric development.

Future research should focus on developing unified conceptual and operational frameworks for socio-economic centrality, integrating temporal dynamics and cross-scalar interactions more explicitly. Greater attention should also be given to underrepresented geographical contexts to ensure more globally inclusive knowledge production. Finally, further methodological exploration of artificial intelligence tools, including more transparent and explainable LLM frameworks, is needed to strengthen their role in advancing urban research and supporting evidence-based decision-making.

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Conflicts of Interest

The authors report no conflicts of interest.

Data Availability Statement

The data underlying this study, including raw datasets, analytical code, and supplementary research materials, are not publicly deposited but are available from the corresponding author upon reasonable request. Requests will be considered on an individual basis, subject to any applicable ethical, privacy, or institutional restrictions.

CRediT Author Statement

Author1: Methodology; Investigation; Data analysis; Data Visualization; Writing.
Author2: Supervision
Author3: Supervision
Author4: Supervision
All authors have reviewed and approved the final version of the manuscript.

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