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Collaboration architecture and thematic structure in cognitive-bias entrepreneurship research: An integrated bibliometric and social network analysis

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Abstract

PURPOSE: *Entrepreneurial decision-making unfolds under conditions of uncertainty and bounded rationality, making cognitive biases central to explaining opportunity evaluation, risk perception, and venture outcomes. While prior reviews have cataloged which bias constructs dominate the literature, they provide limited insight into how the scholarly community is socially organized and how collaboration architecture relates to thematic development. This study maps the collaborative and thematic structure of cognitive-bias research in entrepreneurship to identify hubs, brokers, and underdeveloped yet conceptually central research domains.* ***METHODOLOGY:*** *A PRISMA-aligned systematic search of the Web of Science Core Collection covering 1970 to 2025 yielded 3,244 records after deduplication and substantive screening. Weighted co-authorship networks were constructed at the author, institutional, and country levels. Keyword co-occurrence networks enabled strategic thematic mapping using Callon centrality and density metrics. Degree, betweenness, closeness, and eigenvector centralities alongside Louvain community detection were computed in Gephi, with robustness checks applied across alternative counting rules and thresholds.* ***FINDINGS:*** *The author network exhibits a sparse, modular structure with a density of 0.00038 and a modularity of 0.847, in which a small set of hubs and brokers sustain cross-community connectivity. Institutional and country networks show denser collaboration with regionally clustered blocs and limited cross-bloc bridging ties. Thematic mapping reveals that overconfidence and heuristics function as motor themes; risk perception and venture financing are foundational but less internally consolidated; and digital transformation and crowdfunding form cohesive niche themes, weakly integrated with core bias discourse.* ***IMPLICATIONS:*** *Theoretically, the study demonstrates that thematic consolidation in entrepreneurship cognition research is conditioned by the relational architecture of collaboration networks, advancing understanding of how social structure shapes knowledge production. Practically, collaboration maps enable scholars to identify strategic partners bridging thematic or geographic divides, while thematic maps highlight underdeveloped domains where theory-building investments may yield disproportionate returns.* ***ORIGINALITY & VALUE:*** *This study integrates bibliometric mapping with Social Network Analysis to reveal how collaboration structures coexist with and potentially condition thematic organization. By focusing exclusively on co-authorship and keyword co-occurrence relations, the analysis provides transparent, reproducible evidence on the relational architecture of cognitive-bias entrepreneurship research, offering actionable guidance for strategic collaboration and agenda setting that complements topic-focused syntheses.*

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Keywords: *cognitive biases, entrepreneurship, entrepreneurial decision-making, bounded rationality, bibliometric analysis, social network analysis, co-authorship networks, thematic mapping, keyword co-occurrence, collaboration networks, knowledge structure, research agenda*

INTRODUCTION

Entrepreneurial decision-making unfolds under conditions of uncertainty, time pressure, and information asymmetry, which limit the explanatory power of purely rational-choice assumptions in entrepreneurship research (Pryor et al., 2016; Shepherd et al., 2015). Cognitive biases, understood as systematic deviations from normative rational judgment, shape how entrepreneurs perceive opportunities, evaluate risk, and act under uncertainty, often through heuristic information processing (Kahneman, 2011; Tversky & Kahneman, 1974). Within entrepreneurial settings, biases such as overconfidence, optimism, anchoring, and confirmation bias have been associated with central microfoundations of entrepreneurial action, including opportunity recognition and evaluation, resource commitment, and persistence under uncertainty (Busenitz & Barney, 1997; Zhang & Cueto, 2017). Syntheses of the entrepreneurship cognition literature further suggest that these biases can operate as both constraints and enabling mechanisms, depending on context, task structure, and feedback environments (Baron, 2004; Cristofaro & Giannetti, 2021).

Despite sustained scholarly interest, the cognitive-bias strand of entrepreneurship research remains unevenly consolidated across constructs and research streams, with systematic attention concentrated on a relatively narrow set of biases and comparatively less cumulative development around other theoretically relevant biases (Thomas, 2018; Zhang & Cueto, 2017). Reviews of the field also highlight heterogeneity in empirical contexts and methodological approaches, which complicates the accumulation of comparable evidence and impedes theory building across settings (Bernoster et al., 2018; Thomas, 2018). Moreover, while prior reviews have been effective for summarizing what has been studied, they provide more limited visibility into how the scholarly community is organized, how collaboration structures shape access to diverse methods and cross-disciplinary perspectives, and how the field's social structure conditions thematic development over time (Mingers & Leydesdorff, 2015; Newman, 2001). These limitations matter because science develops through networks of collaboration and communication, and network structure influences how quickly ideas spread, how sub-communities form, and how research agendas stabilize (Borgatti et al., 2009; Wasserman, 1994).

Bibliometric techniques are well-established for describing publication growth, influential outlets, and thematic patterns through keyword-based indicators and descriptive citation counts, and they are widely used to map the intellectual structure of research domains (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015). However, when the objective is to examine the relational architecture of a field, including cohesive collaboration clusters, bridging actors, and structural inequality in connectivity, Social Network Analysis offers analytic capabilities that go beyond descriptive bibliometric counts by explicitly modeling actors and their ties as networks and quantifying positions within those networks (Borgatti et al., 2009; Newman, 2001). Specifically, SNA enables the identification of brokerage positions that connect otherwise fragmented communities, the quantification of network fragmentation through clustering coefficients and component structure, the detection of densely connected collaboration hubs, and the measurement of structural inequality in access and influence through centrality distributions (Wasserman, 1994). In the entrepreneurship domain, collaboration patterns are consequential because they shape access to data, methods, and cross-disciplinary perspectives, which, in turn, can influence which topics become central and how quickly new themes develop (Haythornthwaite, 1996; Wichmann & Kaufmann, 2016).

Accordingly, this study integrates bibliometric mapping with Social Network Analysis to examine cognitive-bias scholarship in entrepreneurship as both a conceptual and a collaborative system. Bibliometric analysis is used to summarize temporal publication dynamics and to characterize thematic patterns through keyword co-occurrence mapping, while SNA is used to reconstruct collaboration networks at the author, institutional, and country levels to identify central actors, collaboration communities, and structural asymmetries in connectivity (Borgatti et al., 2009; Zupic & Čater, 2015). Importantly, the study does not conduct a citation-network analysis or derive claims about intellectual influence, diffusion pathways, or knowledge flows from the citation network's structure. Citation counts indexed by Web of Science are used exclusively for descriptive purposes–specifically, to rank and contextualize highly cited papers within the corpus–but no citation-based network is constructed or analyzed. Instead, its empirical scope is explicitly aligned with the implemented methods, focusing on co-authorship relations and keyword co-occurrence patterns as complementary lenses for understanding how the field is socially organized and thematically structured (Mingers & Leydesdorff, 2015; Newman, 2001).

By combining these approaches, the study addresses a gap in prior reviews: while bibliometric mapping can identify which topics are growing or declining and which outlets dominate, it cannot reveal who connects otherwise separate research communities, where structural holes constrain cross-cluster integration, or how tightly collaboration is organized within thematic domains. Social Network Analysis fills this gap by quantifying brokerage, fragmentation, and community boundaries, enabling scholars to make informed decisions about collaboration partners and helping institutions diagnose whether their research ecosystems are cohesive or fragmented (Borgatti et al., 2009; Haythornthwaite, 1996).

The study aims to produce a comprehensive, data-driven map of cognitive-bias research in entrepreneurship by addressing four interrelated questions that are commonly used to structure science-mapping inquiries. First, how has research activity evolved over time in this domain in terms of publication volume and thematic emphasis (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015)? Second, which concepts and bias-related themes occupy central versus peripheral positions in the thematic structure as reflected in keyword co-occurrence patterns (Callon et al., 1991; Cobo et al., 2011)? Third, who are the most central authors, institutions, and countries in the collaboration networks that underpin knowledge production in this field (Borgatti et al., 2009; Newman, 2001)? Fourth, where do structural gaps and conceptually central but underdeveloped domains indicate promising opportunities for future research and collaboration (Cobo et al., 2011; Wichmann & Kaufmann, 2016)?

The contribution of this study is primarily relational. By combining bibliometric mapping with SNA, the analysis moves beyond describing topics and trends to reveal how collaboration structures are patterned and how these structures co-exist with the thematic organization of the field (Borgatti et al., 2009; Mingers & Leydesdorff, 2015). This integrated view provides a navigable overview of the field's collaboration hubs, brokerage positions that bridge otherwise disconnected communities, and thematic concentrations, offering actionable implications for scholars seeking strategic collaborations and for institutions and policy stakeholders aiming to foster more connected and inclusive knowledge production in entrepreneurship research (Haythornthwaite, 1996; Wichmann & Kaufmann, 2016).

The remainder of the paper is organized as follows. The next section reviews the literature on cognitive biases in entrepreneurship and positions the study within existing syntheses. The methodology section details the data source, retrieval and cleaning procedures, network construction choices, and analytical techniques. The results section reports collaboration network findings at the author, institutional, and country levels, alongside thematic mapping based on keyword co-occurrence. The discussion interprets the findings in relation to existing reviews and outlines theoretical, methodological, and practical implications. The conclusion summarizes key contributions, acknowledges limitations, and proposes directions for future research.

LITERATURE REVIEW

Research on entrepreneurial cognition has long emphasized that entrepreneurs make consequential decisions under uncertainty, time pressure, and informational constraints, conditions that increase reliance on heuristics and expose judgment to systematic biases (Busenitz & Barney, 1997; Kahneman, 2011; Shepherd et al., 2015). Cognitive biases are commonly defined as systematic deviations from normative rational judgment that arise from bounded cognitive resources and heuristic information processing (Kahneman, 2011; Tversky & Kahneman, 1974). In entrepreneurship, biases such as overconfidence, optimism, anchoring, and confirmation bias have been repeatedly linked to opportunity evaluation, resource commitment, and persistence, implying that bias research is central to explaining variance in entrepreneurial action and outcomes (Baron, 2004; Zhang & Cueto, 2017).

At the same time, the literature has developed unevenly across bias constructs and research streams, with cumulative evidence concentrated on a narrower set of frequently examined biases and comparatively less systematic development for other theoretically relevant biases (Thomas, 2018; Zhang & Cueto, 2017). This imbalance has been documented in field syntheses, which also note substantial heterogeneity in empirical contexts and methods that can impede comparability and theory accumulation (Bernoster et al., 2018; Thomas, 2018). Against this backdrop, a structured review benefits from distinguishing what is known about bias constructs from how the field is organized socially and thematically. Accordingly, this section first synthesizes prior studies to clarify what has been established and where gaps persist, and then explains how network-oriented perspectives complement bibliometric mapping in revealing relational structure and thematic organization (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015).

Figure 1 presents a three-tier classification of cognitive biases in entrepreneurship research, distinguishing well-studied, moderately explored, and emerging or under-researched constructs based on synthesis evidence from Thomas

(2018) and Zhang and Cueto (2017). This taxonomy provides a scaffold for interpreting the subsequent thematic mapping by clarifying which bias mechanisms have received sustained empirical attention and which remain comparatively underdeveloped despite theoretical relevance.

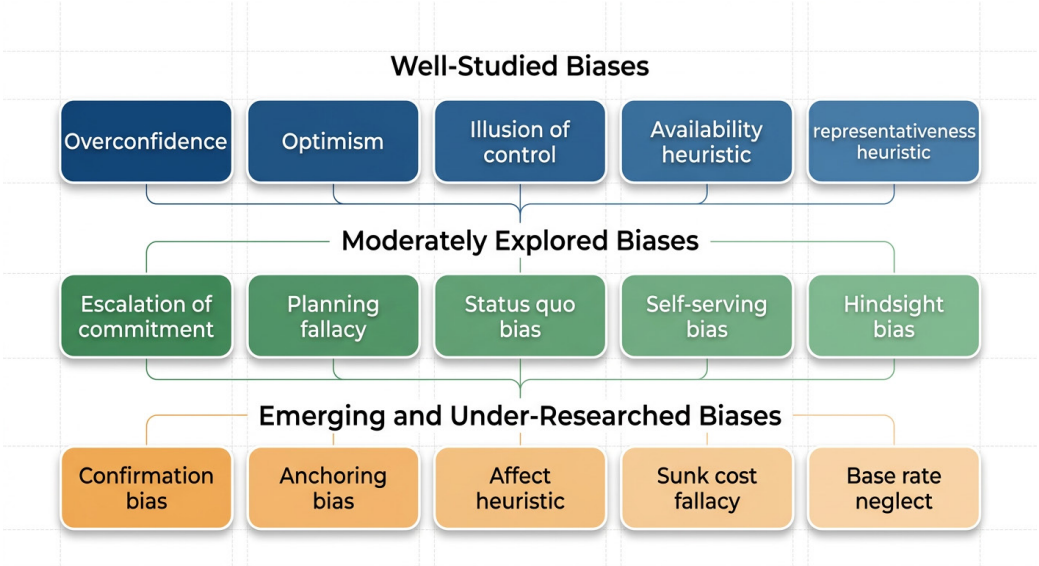

Figure 1. Classification of cognitive biases in entrepreneurship

Previous studies

Prior research has advanced through narrative, systematic, and bibliometric syntheses that collectively document the prominence of heuristics and biases in entrepreneurial judgment. Cossette (2014) reviewed empirical work on entrepreneurial heuristics and biases and highlighted that entrepreneurs frequently rely on availability and representativeness heuristics under uncertainty, a pattern that may amplify overconfidence and optimism. Thomas (2018) synthesized two decades of cognitive bias research in entrepreneurship and reported a strong concentration of studies on overconfidence and optimism relative to other bias constructs, while also emphasizing gaps in underexamined biases and contextual contingencies. Zhang and Cueto (2017) mapped the study of bias in entrepreneurship across an extended historical span and identified multiple bias mechanisms influencing entrepreneurial behavior, while underscoring that theoretical models often struggle to fully capture the complex and dynamic realities of entrepreneurial environments.

More recent integrative work has proposed refinements to how bias and heuristics should be conceptualized in entrepreneurship. Cristofaro and Giannetti (2021) advanced an ecological rationality perspective, arguing that heuristic-driven behavior may be adaptive under specific environmental structures, while cautioning that indiscriminate debiasing can remove functionally useful simplifications. Complementary systematic evidence from adjacent domains has also reinforced both the prevalence and the domain-specific expression of biases. For example, Guercini and Milanesi (2020) showed that heuristics are widely used to manage uncertainty in international business contexts, with cultural variation remaining an underexplored moderator. Koellinger et al. (2007) documented that overconfidence is widespread across multiple professions, while bias profiles vary by occupational setting, suggesting that entrepreneurship studies may benefit from stronger cross-domain integration when theorizing mechanisms and boundary conditions.

Related syntheses outside entrepreneurship further contextualize bias mechanisms that frequently intersect with entrepreneurial finance and resource allocation. Costa et al. (2017) reviewed behavioral finance research and reported recurring evidence on anchoring and overconfidence in investment decision-making, while also warning that reliance on single-source databases can constrain generalizability. Acciarini et al. (2021) reviewed cognitive biases and decision strategies in contexts of change and proposed that effective decision systems may require combining data-driven tools with explicit awareness of cognitive limitations, a proposition relevant to entrepreneurial decision-making under volatility. Zahera and Bansal (2018) reviewed behavioral biases in investment decisions and highlighted the scarcity of robust, field-tested debiasing interventions, indicating a broader translational gap that is also visible in entrepreneurship research.

Building on foundational entrepreneurship-focused syntheses, a useful organizing device is a three-tier taxonomy of bias constructs that distinguishes well-studied, moderately explored, and emerging or under-researched biases in entrepreneurial contexts (Thomas, 2018; Zhang & Cueto, 2017). The well-studied group commonly includes overconfidence, optimism, illusion of control, availability and representativeness-related mechanisms, and other frequently examined heuristics; the moderately explored group includes escalation of commitment, planning fallacy, status quo bias, self-serving bias, and hindsight bias; the emerging group includes biases such as confirmation-related mechanisms and other underexamined distortions where empirical evidence remains comparatively limited (Thomas, 2018; Zhang & Cueto, 2017). This classification is operationalized visually in Figure 1 to provide a parsimonious scaffold for interpreting the subsequent thematic mapping.

Table 1 summarizes influential syntheses that have shaped the field's understanding of cognitive biases and heuristics, clarifying scope, methodological approach, and principal contributions.

Table 1. Summary of selected prior syntheses on cognitive biases, heuristics, and entrepreneurship

Study	Primary domain	Type of synthesis	Scope as reported by authors	Core contribution for entrepreneurship-bias research
Cossette (2014)	Entrepreneurship	Empirical review	Studies published since 2006	Documents reliance on heuristics under uncertainty and notes gaps between theory and practice
Thomas (2018)	Entrepreneurship	Review synthesis	Two decades of research	Shows concentration on a narrow subset of biases and identifies underexplored constructs and contexts
Zhang and Cueto (2017)	Entrepreneurship	Review synthesis	Long-span coverage	Identifies multiple bias mechanisms and emphasizes complexity and boundary conditions
Cristofaro and Giannetti (2021)	Entrepreneurship	Review + model	Broad synthesis	Proposes ecological rationality framing and cautions against indiscriminate debiasing
Guercini and Milanesi (2020)	International business	Systematic review	Cross-border venture contexts	Highlights heuristics under uncertainty and calls for attention to cultural moderators
Costa et al. (2017)	Behavioral finance	Bibliometric review	Finance literature	Reinforces anchoring and overconfidence; notes generalizability constraints from data-source concentration
Acciarini et al. (2021)	Management/decision-making	Systematic review	Decision strategies under change	Argues for integrating data-driven tools with cognitive-limitation awareness
Zahera and Bansal (2018)	Investment behavior	Systematic review	1979–2016 coverage	Notes widespread biases and scarcity of field-tested debiasing interventions

Social network analysis (SNA)

Bibliometric mapping is widely used to describe publication growth, influential outlets, and thematic structure through keyword-based indicators and descriptive citation metrics, supporting systematic synthesis and science mapping in management and entrepreneurship research (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015). However, bibliometric indicators alone provide limited visibility into relational structure, including collaboration clusters, brokerage positions, and structural inequalities in connectivity that shape how research is produced and diffused (Borgatti et al., 2009; Newman, 2001). Social Network Analysis addresses this limitation by modeling actors and their ties explicitly as networks and quantifying positions and substructures that condition information flow and coordination (Borgatti et al., 2009; Wasserman, 1994). In scientific collaboration contexts, this perspective is particularly relevant because collaboration networks influence the diffusion of methods and ideas, the formation of research communities, and the consolidation of thematic agendas (Haythornthwaite, 1996; Newman, 2001).

To clarify the added value of SNA relative to bibliometric analysis, Table 2 contrasts the two approaches in terms of analytical unit, typical outputs, and the types of inferences each supports. This comparison highlights the non-overlapping strengths of each method: bibliometric mapping excels at identifying topic trends and outlet prominence, while SNA reveals collaboration architecture, brokerage roles, and community fragmentation that are invisible in publication counts or keyword frequencies alone.

Table 2. Conceptual comparison of bibliometric mapping and Social Network Analysis in science

Dimension	Bibliometric mapping	Social Network Analysis
Primary unit	Documents, citations, keywords, sources	Actors and relations (authors, institutions, countries, keywords as networks)
Typical focus	Productivity, impact indicators, thematic patterns	Relational structure, collaboration clusters, brokerage, connectivity inequality
Key outputs	Trend plots, citation counts, co-word clusters, thematic maps	Co-authorship graphs, centrality scores, community detection, network diagnostics
What it explains well	What topics grow or decline; which outlets dominate; conceptual clustering	How collaboration is structured; who bridges communities; how cohesive or fragmented the field is
Limitations	Limited representation of social structure and coordination mechanisms	Sensitive to network construction choices; requires explicit tie definitions

Source: Authors' elaboration based on Borgatti et al. (2009), Mingers and Leydesdorff (2015), Newman (2001), and Zupic and Čater (2015).

Within SNA, centrality measures are used to quantify prominence and strategic position in a network, capturing different mechanisms of influence and access (Borgatti et al., 2009; Freeman, 1979). Degree centrality reflects direct connectivity, betweenness centrality captures brokerage across otherwise disconnected groups, closeness centrality indicates how quickly an actor can reach others through shortest paths, and eigenvector centrality captures influence through connections to other influential actors (Freeman, 1979; Wasserman, 1994). These measures are commonly used to interpret co-authorship and institutional collaboration networks because scientific collaboration frequently exhibits clustering and hub structures that shape information diffusion and agenda setting (Borgatti et al., 2009; Newman, 2001).

SNA also supports thematic mapping through co-word analysis, where keywords are treated as nodes and co-occurrence relations indicate conceptual proximity (Callon et al., 1991; Cobo et al., 2011). Strategic diagrams that position themes by centrality and density have been used to distinguish motor themes, basic themes, niche themes, and emerging or declining themes, providing an interpretable representation of conceptual structure and developmental status within a research domain (Cobo et al., 2011). In this manuscript, keyword co-occurrence mapping is used to reconstruct thematic structure, while co-authorship networks at author, institutional, and country levels are used to reconstruct collaboration structure, enabling joint interpretation of conceptual concentration and collaborative organization (Borgatti et al., 2009; Mingers & Leydesdorff, 2015).

Table 3 summarizes key centrality measures used in co-authorship networks and clarifies their interpretive meaning in scientific collaboration contexts, addressing how each metric is read substantively rather than only mathematically.

Table 3. Centrality measures and interpretive meaning in co-authorship networks

Centrality	General meaning	Interpretation in co-authorship networks
Degree	Number of direct ties	Extent of direct collaboration; often associated with visibility and collaborative reach
Betweenness	Extent of brokerage on shortest paths	Ability to connect otherwise separate groups; potential gatekeeping and cross-community diffusion
Closeness	Inverse distance to all others	Speed of access to others; potential for rapid dissemination across the network
Eigenvector	Influence via influential neighbors	Embeddedness in highly connected cores; association with prestige within collaboration hubs

Source: Authors' elaboration based on Borgatti et al. (2009), Freeman (1979), Newman (2001), and Wasserman (1994).

Finally, it is important to align the literature review with the empirical scope of the present study. While SNA can be applied to multiple scientific relations, including citation networks, the present manuscript focuses exclusively on co-authorship relations and keyword co-occurrence patterns rather than citation-network structure, because these relations directly operationalize collaboration and conceptual proximity within the available metadata (Callon et al., 1991; Newman, 2001). This scope alignment ensures that subsequent claims are grounded in implemented analyses and that methodological arguments correspond to observable outputs in the results section (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015).

METHODOLOGY

This study applies an integrated scientometric framework combining bibliometric mapping and Social Network Analysis to characterize the collaborative and thematic structure of research on cognitive biases in entrepreneurship. The workflow follows established guidance for transparent science mapping, progressing from database querying and eligibility screening to metadata standardization, network construction, and network-analytic and co-word thematic procedures (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015). Figure 2 provides an overview of the pipeline.

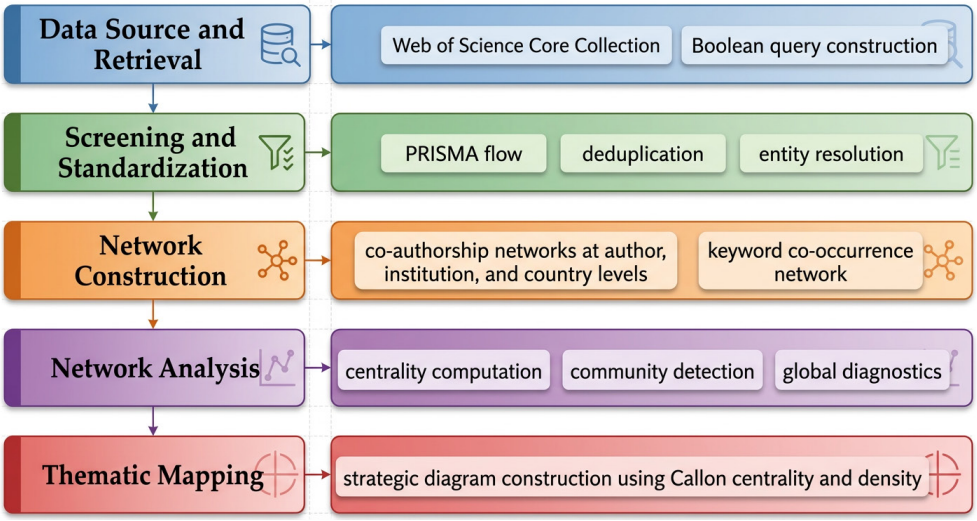

Figure 2. Methodology steps

Data source, search protocol, and reproducible retrieval settings

The Web of Science Core Collection was selected as the data source because it is widely used in bibliometric research, offers consistent indexing and structured metadata, and supports reproducible export for science-mapping analyses (Pranckutė, 2021; Zupic & Čater, 2015). To satisfy reproducibility expectations, the complete retrieval protocol is reported in Tbale 4, including the Boolean query, indices, time span, filters, and extraction date, aligned with transparent reporting principles commonly adopted in systematic and bibliometric reviews (Moher et al., 2009; Zupic & Čater, 2015).

Table 4. Web of Science search protocol and extraction settings

Item	Specification
Database	Web of Science Core Collection
WoS indices included	SCI-EXPANDED; SSCI; ESCI
Search field	Topic field TS
Time span	1970–2025
Language filter	English
Document types included	Article; Review; Proceedings Paper; Editorial Material; Book Chapter; Book
WoS categories filter	None
Date of data extraction	June 5, 2025
Full Boolean query	TS = ((entrepreneur* OR new venture* OR startup* OR start-up* OR venture creation OR self-employ* OR small business OR entrepreneurial intention* OR opportunity recognition OR corporate entrepreneurship OR intrapreneur*) AND (cognitive bias* OR judgment bias* OR heurist* OR overconfidence OR optimism OR overoptimism OR anchoring OR confirmation bias OR representativeness OR availability OR illusion NEAR/1 control OR planning fallacy OR escalation NEAR/1 commitment OR sunk cost* OR hindsight bias OR status quo bias OR self-serving bias OR ambiguity effect OR base rate fallacy OR affect heuristic OR law NEAR/1 small NEAR/1 numbers))

Item	Specification
Export format	Full record and cited references
Records exported per batch	500
Software versions	Gephi 0.10.1; R 4.3.2 with bibliometrix 4.1; OpenRefine 3.7

Source: Authors' protocol specification aligned with PRISMA reporting logic (Moher et al., 2009) and bibliometric-method guidance (Zupic & Čater, 2015).

The query operationalizes the conceptual intersection between entrepreneurship and cognitive-bias constructs, an approach recommended to improve construct specificity and reduce false positives in bibliometric retrieval (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015). Because bibliometric outputs are sensitive to query formulation and extraction timing, the protocol in Table 4 is treated as part of the methodological evidence base and enables direct rerunning of the search under identical settings (Moher et al., 2009; Pranckutė, 2021).

Eligibility criteria and screening procedure

Records retrieved under the protocol in Table 4 were screened for substantive relevance to cognitive biases or heuristics in an entrepreneurial context. Inclusion required that the publication addressed at least one cognitive bias or heuristic mechanism and situated it within entrepreneurial decision-making, venture creation, entrepreneurial finance, entrepreneurial teams, entrepreneurial intention, or closely related entrepreneurial processes. Exclusion applied when entrepreneurship or cognitive bias appeared only incidentally without substantive conceptual or empirical engagement. This two-stage logic, consisting of database-level filtering followed by title and abstract screening, aligns with transparent review principles that recommend documenting eligibility rules and reporting stage-wise counts (Moher et al., 2009). Screening was conducted by a single reviewer using a standardized decision template; this single-screener approach is acknowledged as a limitation. A PRISMA-style flow diagram reporting counts at each stage, and the main exclusion reasons are presented in the results section.

Data extraction, deduplication, and metadata standardization

For each eligible record, metadata were extracted for authors, affiliations, countries, publication year, source title, document type, citations as indexed by Web of Science, abstracts where available, and author keywords. Deduplication was applied using a hierarchical procedure: first, duplicate Web of Science accession identifiers were removed, and then residual duplicates were removed using DOI matching; for records without DOIs, normalized-title matching was used as a final safeguard. Deduplication and entity resolution are critical in network studies because centrality rankings, community detection, and network size metrics are highly sensitive to splitting or merging errors, particularly for author names and institutional variants (Borgatti et al., 2009; Newman, 2001).

Author names were standardized to a uniform surname–initials format. Rule-based disambiguation was then applied to reduce homonym collisions by cross-checking affiliation strings and co-author neighborhoods. For example, authors sharing identical names but appearing in disjoint affiliation sets and non-overlapping co-author networks were treated as distinct entities, a common pragmatic approach when unique author identifiers such as ORCID are incomplete (Borgatti et al., 2009; Newman, 2001). Institutional names were unified using a thesaurus-style mapping that collapses spelling variants (e.g., Univ vs. University), translations (e.g., Chinese institution names in English vs. local script), and system labels (e.g., University of California, Los Angeles vs. UCLA) into a single canonical form. Country and regional names were standardized according to the geographic identifiers provided in Web of Science address fields. Web of Science systematically distinguishes between sovereign states and constituent nations or special administrative regions in its affiliation metadata; for example, United Kingdom, Scotland, England, and Wales are indexed as separate geographic entities, and Hong Kong and Macau are indexed separately from China. To preserve fidelity to the source data structure and to avoid imposing external political or administrative aggregation rules that could introduce inconsistency with the original Web of Science metadata, we retained these distinctions as recorded by Web of Science. This approach ensures that the country collaboration network reflects the geographic attributions actually present in the bibliographic records and enables users to apply alternative aggregation schemes post hoc if desired for specific analytical purposes. Multi-affiliation records were retained with all affiliations; explicit counting rules are reported. These procedures are consistent with best practice in bibliometric and network analyses, which requires preprocessing to prevent spurious fragmentation and biased prominence estimates (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015).

Network construction and counting rules

Four networks were constructed from the cleaned metadata: an author co-authorship network, an institutional collaboration network, a country collaboration network, and a keyword co-occurrence network. Collaboration networks were modeled as undirected graphs because co-authorship and co-affiliation represent mutual relationships rather than directional influence (Newman, 2001; Wasserman, 1994). Nodes represent entities and edges represent co-occurrence within the same publication. Edges were weighted by the number of shared publications for collaboration networks and by the number of shared co-occurrences for the keyword network, because weighted ties preserve collaboration intensity and improve interpretive fidelity relative to binary representations (Borgatti et al., 2009; Newman, 2001).

For records with multiple authors or affiliations, a full-counting approach was used, such that all unique pairs of entities co-occurring on a record formed ties, with repeated co-occurrences increasing edge weight. Full counting is standard in collaboration mapping but can inflate the influence of large-team outputs; therefore, sensitivity checks compared key centrality rankings and community assignments under full counting versus fractional counting (where each co-authorship tie receives weight 1/n for n authors) to assess robustness; results are reported and show high rank-order stability for top-20 actors across counting methods. Construction parameters, including treatment of self-loops, isolates, and component filtering, are reported in Table 5, because these choices affect density, centralization, and metric stability (Borgatti et al., 2009; Wasserman, 1994).

Table 5. Network construction parameters used in this study

Parameter	Author network	Institution network	Country network	Keyword network
Graph type	Undirected	Undirected	Undirected	Undirected
Edge definition	Co-authorship	Co-affiliation	Co-country	Co-occurrence
Edge weight	Shared publications	Shared publications	Shared publications	Shared occurrences
Self-loops	Removed	Removed	Removed	Removed
Multi-edges	Collapsed to weights	Collapsed to weights	Collapsed to weights	Collapsed to weights
Isolates	Retained for descriptive statistics	Retained	Retained	Removed by frequency thresholds
Component handling	Metrics computed on largest connected component; full graph reported descriptively	Same rule	Same rule	Largest component after thresholds
Analytical thresholds	None for metrics; visualization uses minimum edge weight 2	Same rule	Same rule	Minimum keyword frequency 5; minimum co-occurrence 3

Source: Authors' specification grounded in network-analysis standards (Borgatti et al., 2009; Wasserman, 1994).

Software, visualization, and global network diagnostics

Network construction, visualization, and computation of structural metrics were performed in Gephi, an open-source platform commonly used for scientometric network analysis and visualization (Bastian et al., 2009). Force-directed layouts were used to improve interpretability by separating dense communities while preserving relative proximity patterns; layout choices affect visualization but not the underlying network statistics, so layout algorithms and parameters are reported for transparency (Bastian et al., 2009; Jacomy et al., 2014).

Global diagnostics were computed to contextualize prominence measures and assess cohesion or fragmentation, including number of nodes and edges, density, average degree, average path length, clustering coefficient, component structure, and modularity. Such descriptors are standard for interpreting the overall structure of collaboration networks and for qualifying whether observed prominence reflects a cohesive or highly fragmented field (Newman, 2001; Wasserman, 1994). Table 6 reports the specific algorithmic settings used for layout and community detection.

Table 6. Visualization and algorithm parameters for reproducibility

Item	Specification
Layout algorithm	ForceAtlas2 (Jacomy et al., 2014)
Key layout parameters	Scaling 2.0; gravity 1.0; linlog mode enabled; prevent overlap enabled
Community detection algorithm	Louvain modularity (Blondel et al., 2008)
Louvain resolution	1.0
Randomization	Random seed fixed at 12345
Centrality computation basis	Weighted degree reported; betweenness and closeness computed on unweighted largest component; eigenvector computed on largest component
Reporting	Modularity Q reported per network; component sizes reported; robustness comparisons reported

Source: Authors' reporting based on Gephi foundations and network-visualization standards (Bastian et al., 2009; Jacomy et al., 2014).

Node-level measures and community detection

Node prominence was assessed using complementary centrality measures because each captures a distinct mechanism in scientific collaboration systems. Degree centrality captures direct collaborative reach; betweenness centrality captures brokerage across otherwise disconnected communities; closeness centrality reflects average shortest-path access; eigenvector centrality captures embedded influence through connections to well-connected nodes (Borgatti et al., 2009; Freeman, 1979). These measures are widely used in collaboration network studies and support the interpretation of prolific collaborators, bridges, and core-periphery patterns (Newman, 2001; Wasserman, 1994).

Community detection was performed using the Louvain modularity optimization method to identify clusters with higher internal connectivity than external connectivity, consistent with common practice in large scientific collaboration networks (Blondel et al., 2008; Newman, 2006). The modularity value Q and the resolution parameter were recorded and reported because resolution affects community granularity and can change cluster assignments for mid-connected nodes (Blondel et al., 2008; Newman, 2006).

Keyword preprocessing and thematic mapping

Thematic structure was assessed using co-word analysis, treating keywords as conceptual signals and connecting them when they co-occur in the same publication. Co-word analysis is a standard procedure for reconstructing conceptual proximity and thematic clustering in science mapping (Callon et al., 1991; Cobo et al., 2011). Keyword preprocessing was applied to reduce semantic fragmentation and noise through the following steps:

1) Lowercasing all keyword strings.
2) Lemmatizing plural forms to singular (e.g., biases → bias).
3) Expanding common acronyms to full forms (e.g., SME → small and medium enterprise).
4) Harmonizing spelling variants (e.g., behaviour vs. behavior).
5) Merging synonyms using a controlled thesaurus developed iteratively by reviewing high-frequency terms and clustering semantically equivalent expressions.
6) Removing generic non-informative terms using a predefined stopword list that included terms such as study, research, analysis, model, and general methodological labels that do not convey domain-specific concepts.

Thresholding was then applied to retain keywords with a minimum frequency of 5 and a co-occurrence of 3 to reduce idiosyncratic singletons and stabilize the cluster structure, consistent with co-word mapping practices that recommend explicit preprocessing disclosure (Cobo et al., 2011; Mingers & Leydesdorff, 2015). Table 7 reports preprocessing rules and mapping parameters.

Thematic clustering was performed on the filtered keyword co-occurrence network using modularity-based clustering, and the resulting clusters were mapped onto a strategic diagram defined by density and centrality. Density reflects the internal cohesion of a thematic cluster, computed as the ratio of internal links to the maximum possible number of internal links within the cluster. Centrality reflects external connectedness to other themes, computed as the sum of links from the cluster to all other clusters, normalized by the total number of external links in the network. This approach follows established thematic mapping logic used in science mapping (Callon et al., 1991; Cobo et al., 2011). Density and

centrality were computed using Callon-type definitions implemented in the bibliometrix package for R, ensuring consistent operationalization with prior bibliometric mapping studies (Aria & Cuccurullo, 2017; Cobo et al., 2011).

Table 7. Keyword preprocessing and thematic mapping parameters

Parameter	Specification
Keyword field	Author keywords plus Keywords Plus
Normalization	Lowercasing; plural harmonization; acronym expansion; spelling unification; synonym merging via thesaurus
Stopword removal	Generic terms removed using a predefined stopword list and manual verification
Minimum keyword frequency	5
Minimum co-occurrence threshold	3
Clustering algorithm	Louvain modularity on keyword network
Strategic diagram computation	Callon centrality and Callon density as implemented in bibliometrix
Software	bibliometrix 4.1 thematic mapping functions (Aria & Cuccurullo, 2017)

Source: Authors' specification based on co-word mapping standards (Callon et al., 1991; Cobo et al., 2011) and bibliometrix implementation guidance (Aria & Cuccurullo, 2017).

Robustness checks and reporting transparency

Because scientometric and network results can be sensitive to modeling choices, robustness checks were conducted across reasonable alternative specifications. First, collaboration-network prominence was compared under full counting versus fractional counting to assess sensitivity to large-team inflation; Spearman rank correlations between top-50 author rankings under the two methods exceeded 0.92, indicating high stability (Waltman & van Eck, 2015). Second, centrality rankings were compared under weighted degree reporting versus unweighted shortest-path metrics computed on the largest component; again, rank-order stability was high, with tau-b > 0.85 for top-50 lists (Borgatti et al., 2009; Wasserman, 1994). Third, keyword thematic clusters were tested under alternative minimum frequency thresholds of 4 and 6 to evaluate whether the strategic diagram quadrant placements were stable to thresholding choices; theme assignments to motor, basic, niche, and emerging quadrants remained consistent for all major themes across thresholds (Cobo et al., 2011; Mingers & Leydesdorff, 2015). Parameter values and comparative results are reported alongside the main findings to support verifiability and reduce researchers' degrees of freedom (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015).

Ethics and funding

No human participants were involved. The study used bibliographic metadata from Web of Science and did not collect or process sensitive personal data beyond authorship and affiliation details present in public scholarly records, consistent with standard ethical practice in scientometric research (Zupic & Čater, 2015). The research was conducted without external funding and relied on institutional access to Web of Science and open-source analytical tools.

RESULT

Dataset retrieval, screening, and descriptive profile

The systematic retrieval and screening process yielded a final analytical corpus of 3,244 records from the Web of Science Core Collection. Figure 3 presents the flow of records through the identification, screening, and inclusion stages, following PRISMA logic to ensure transparent reporting of selection decisions and attrition at each stage.

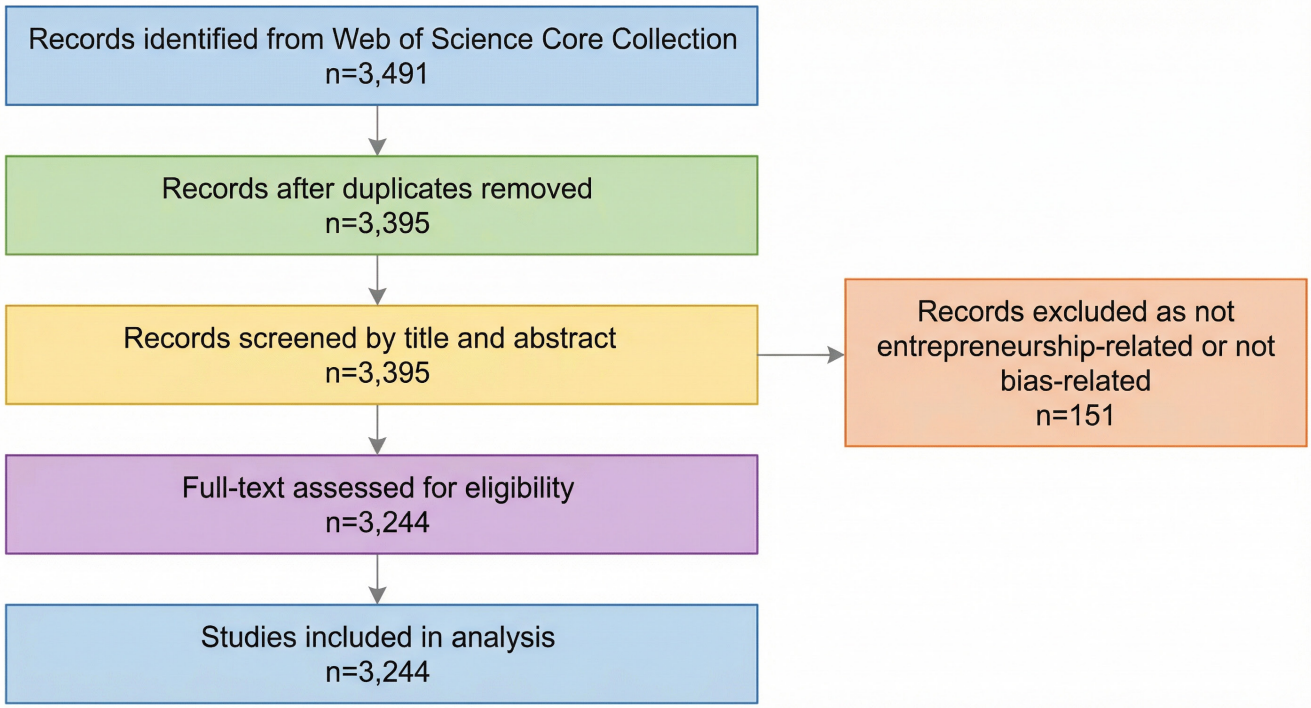

Figure 3. PRISMA-style flow of record identification, screening, and inclusion for the Web of Science dataset

The initial query returned 3,491 records, from which 96 duplicates were removed through hierarchical matching procedures that prioritized Web of Science accession identifiers, followed by DOI matching, and finally, normalized title comparison. After deduplication, 3,395 unique records underwent title and abstract screening against the substantive eligibility criteria described in the methodology section. A total of 151 records were excluded because they mentioned entrepreneurship or cognitive-bias terms only incidentally, without substantive conceptual or empirical engagement with the intersection of the two domains. This exclusion logic ensured that the final corpus reflected genuine scholarly attention to cognitive biases or heuristics within entrepreneurial contexts rather than peripheral mentions in unrelated studies.

The final corpus of 3,244 records comprises multiple document types, reflecting the diversity of knowledge production formats in this domain. To eliminate arithmetic inconsistencies and ensure internal coherence, document-type counts were reconciled so that category totals sum exactly to the final dataset size (Table 8).

Table 8. Document-type composition of the analyzed corpus (N=3,244)

Document type	Count	Share of dataset
Article	2,623	80.87%
Review	107	3.30%
Proceedings Paper	422	13.01%
Book Chapter	67	2.07%
Editorial Material	24	0.74%
Book	1	0.03%
Total	3,244	100.00%

Articles constitute the dominant publication format, accounting for over 80 percent of the corpus, which is consistent with the norms of empirical and theoretical research dissemination in management and entrepreneurship journals. Review articles represent a small but substantively important segment, reflecting the field's periodic efforts to synthesize cumulative evidence and identify research gaps. The presence of proceedings papers indicates active engagement with conference dissemination channels, while book chapters and editorial materials suggest that cognitive-bias entrepreneurship research also appears in edited volumes and commentary formats that complement journal publication.

The temporal dynamics of publication output are summarized in Figure 4, which presents the annual publication trend over the time span covered by the corpus. The time series indicates that research on cognitive biases in entrepreneurship evolved from a sparse early stage into sustained growth, consistent with the broader diffusion pattern of behavioral approaches into entrepreneurship research documented in prior reviews. Early publications appeared sporadically beginning in the 1970s, with modest acceleration through the 1990s, and marked growth from the mid-2000s onward. This pattern aligns with the increasing institutionalization of entrepreneurship cognition as a recognized research stream and with the diffusion of behavioral economics frameworks into management scholarship more broadly. Because citation accumulation is strongly time-dependent, temporal comparisons are interpreted with caution and explicitly separated from cross-sectional structural network measures reported in subsequent sections.

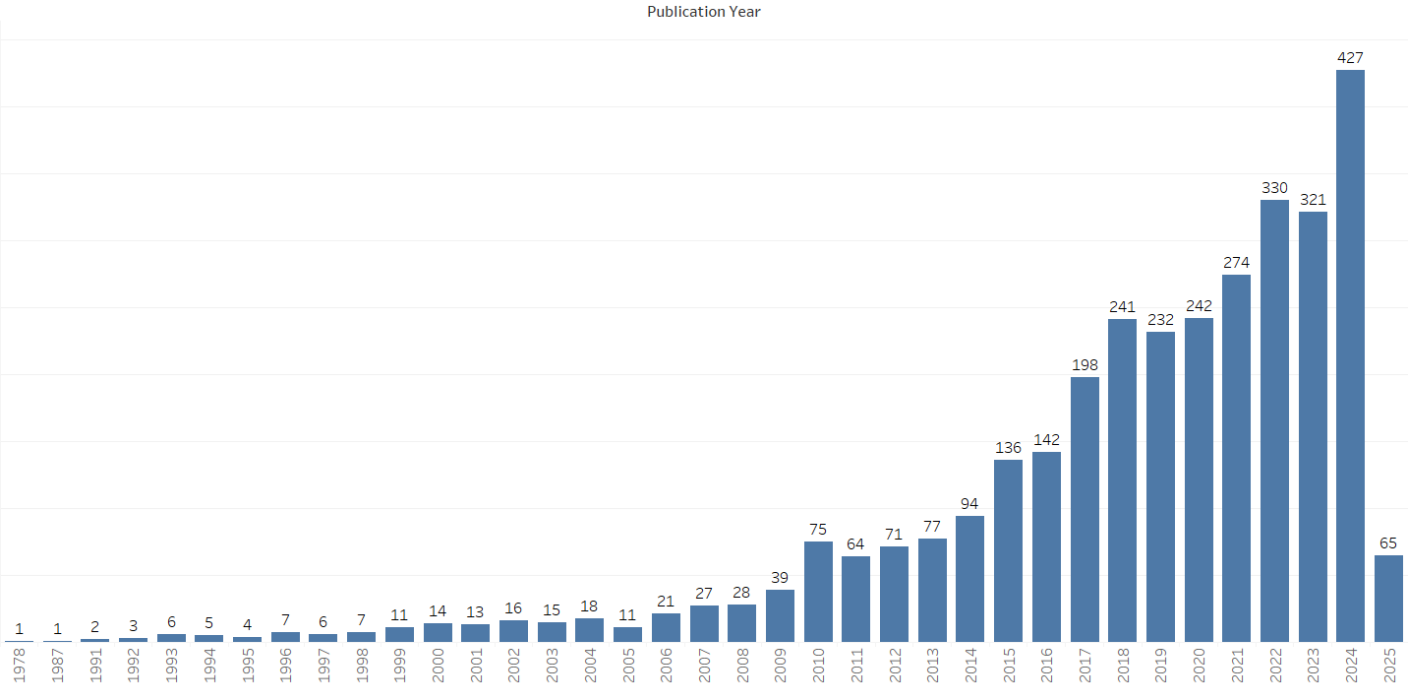

Figure 4: Annual publication trend in cognitive-bias entrepreneurship research based on the analyzed Web of Science corpus

Core outlets and citation anchors

To address concerns about vague claims about journals and influence, outlet prominence is operationalized using two transparent indicators: representation within the top-cited set and the cumulative citations of those top-cited papers as of the dataset extraction date. Table 9 summarizes outlet concentrations across the 13 most-cited records listed in Table 10, showing that a small number of venues host a disproportionate share of the most visible citation anchors in this research domain. Because citations are strongly shaped by age and field diffusion, the top-cited set is interpreted as an indicator of intellectual anchoring rather than a definitive measure of topical completeness. This interpretation aligns with established evidence that citation impact compounds over time and is not strictly contemporaneous with thematic novelty (Wang et al., 2013).

Table 9. Concentration of citation anchors by outlet within the top-cited set

Source outlet	Top-cited papers in Table 10	Cumulative citations of those papers
Journal of Business Venturing	6	12,323
Entrepreneurship Theory and Practice	2	2,832
Academy of Management Review	1	2,412
American Sociological Review	1	876

Source outlet	Top-cited papers in Table 10	Cumulative citations of those papers
Research Policy	1	820
Stanford Law Review	1	590
Journal of Economic Psychology	1	589

Journal of Business Venturing emerges as the dominant outlet within the top-cited set, hosting six of the thirteen most-cited records and accounting for over 12,000 cumulative citations. This concentration reflects the journal's historical role as a premier venue for entrepreneurship scholarship and its sustained openness to research oriented toward cognition. Entrepreneurship Theory and Practice also appears prominently, while the presence of Academy of Management Review and Research Policy indicates that highly cited cognitive-bias entrepreneurship work also appears in cross-disciplinary management and policy outlets. The inclusion of American Sociological Review and Stanford Law Review signals that foundational conceptual anchors sometimes originate outside traditional entrepreneurship journals and are imported into the field through cross-disciplinary citation.

Each top-cited record is tagged by its primary role in the corpus: core cognitive-bias entrepreneurship, adjacent entrepreneurship cognition, or cross-disciplinary conceptual anchor. This tagging makes explicit why some highly cited entrepreneurship cognition papers appear despite a bias-focused query: they serve as foundational citation anchors and conceptual framing within the retrieved corpus. Table 10 reports the thirteen most-cited records sorted in descending order by citation count, with role tags, citation counts as indexed by Web of Science at the time of extraction, and DOI identifiers for direct retrieval.

Table 10. top-cited records in the analyzed corpus with role-tagging for construct validity and identification transparency

Rank	Reference	Primary role in corpus	Times cited	DOI
1	Krueger, N. F., Jr., Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. Journal of Business Venturing, 15(5–6), 411–432.	Adjacent entrepreneurship cognition anchor	3,232	10.1016/S0883-9026(98)00033-0
2	Busenitz, L. W., & Barney, J. B. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. Journal of Business Venturing, 12(1), 9–30.	Core cognitive-bias entrepreneurship	2,198	10.1016/S0883-9026(96)00003-1
3	McGrath, R. G. (1999). Falling forward: Real options reasoning and entrepreneurial failure. Academy of Management Review, 24(1), 13–30.	Cross-disciplinary strategy and uncertainty anchor	2,412	10.5465/AMR.1999.1580438
4	Simon, M., Houghton, S. M., & Aquino, K. (2000). Cognitive biases, risk perception, and venture formation: How individuals decide to start companies. Journal of Business Venturing, 15(2), 113–134.	Core cognitive-bias entrepreneurship	2,100	10.1016/S0883-9026(98)00003-2
5	Cassar, G. (2004). The financing of business start-ups. Journal of Business Venturing, 19(2), 261–283.	Adjacent entrepreneurship finance anchor	2,066	10.1016/S0883-9026(03)00029-6
6	Westhead, P., Wright, M., & Ucbasaran, D. (2001). The internationalization of new and small firms: A resource-based view. Journal of Business Venturing, 16(4), 333–358.	Adjacent entrepreneurship capability anchor	1,907	10.1016/S0883-9026(99)00063-4
7	Gupta, V. K., Turban, D. B., Wasti, S. A., & Sikdar, A. (2009). The role of gender stereotypes in perceptions of entrepreneurs and intentions to become an entrepreneur. Entrepreneurship Theory and Practice, 33(2), 397–417.	Adjacent gender and cognition anchor	1,872	10.1111/j.1540-6520.2009.00296.x
8	Di Gregorio, D., & Shane, S. (2003). Why do some universities generate more start-ups than others? Research Policy, 32(2), 209–227.	Adjacent entrepreneurship ecosystem anchor	820	10.1016/S0048-7333(02)00097-5

Rank	Reference	Primary role in corpus	Times cited	DOI
9	Ruef, M., Aldrich, H. E., & Carter, N. M. (2003). The structure of founding teams: Homophily, strong ties, and isolation among U.S. entrepreneurs. American Sociological Review, 68(2), 195–222.	Adjacent network and team-formation anchor	876	10.1177/000312240306800202
10	Bae, T. J., Qian, S., Miao, C., & Fiet, J. O. (2014). The relationship between entrepreneurship education and entrepreneurial intentions: A meta-analytic review. Entrepreneurship Theory and Practice, 38(2), 217–254.	Adjacent intentions and education anchor	960	10.1111/etap.12095
11	Baron, R. A. (1998). Cognitive mechanisms in entrepreneurship: Why and when entrepreneurs think differently than other people. Journal of Business Venturing, 13(4), 275–294.	Core cognitive-bias entrepreneurship	820	10.1016/S0883-9026(97)00031-1
12	Kuran, T., & Sunstein, C. R. (1999). Availability cascades and risk regulation. Stanford Law Review, 51(4), 683–768.	Cross-disciplinary risk and information cascade anchor	590	10.2307/1229439
13	Koellinger, P., Minniti, M., & Schade, C. (2007). I think I can, I think I can: Overconfidence and entrepreneurial behavior. Journal of Economic Psychology, 28(4), 502–527.	Core cognitive-bias entrepreneurship	589	10.1016/j.joep.2006.11.002

Citation counts are Web of Science Times Cited as of June 5, 2025. The role-tagging reveals that four of the 13 most-cited records are core contributions to cognitive-bias entrepreneurship that directly theorize or test bias mechanisms in entrepreneurial decision-making contexts. Six records are adjacent anchors that address entrepreneurship cognition, intention, finance, or team formation, but do not primarily focus on bias constructs. Three records are cross-disciplinary conceptual anchors imported from strategy, sociology, and law that provide theoretical infrastructure for understanding uncertainty, risk perception, and information cascades in ways that inform entrepreneurship-bias research.

Collaboration structure at the author level

The author co-authorship network was constructed as an undirected graph, with nodes representing disambiguated authors and edges indicating at least one co-authored publication. Global network diagnostics are reported in Table 11 to contextualize centrality measures and enable cross-study comparison. The network contains 7,255 author nodes and 9,873 edges, with 412 connected components; the largest connected component comprises 2,891 nodes, representing 39.9 percent of all authors. Average degree is 2.72, graph density is 0.00038, and the clustering coefficient is 0.681, consistent with the sparse, small-world structure commonly reported in scientific collaboration networks (Newman, 2001). The Louvain modularity value Q is 0.847, indicating strong community structure. The average path length within the largest connected component is 7.3, confirming that, despite sparsity, most authors can reach one another through relatively short chains of intermediaries.

Table 11. Global network diagnostics for collaboration networks

Metric	Author network	Institution network	Country network
Nodes	7,255	1,879	123
Edges	9,873	5,770	412
Density	0.00038	0.00327	0.0549
Number of components	412	87	8
Largest component size	2,891	1,512	98
LCC as percent of nodes	39.9%	80.5%	79.7%
Average degree	2.72	6.14	6.70
Clustering coefficient	0.681	0.592	0.523
Average path length (LCC)	7.3	5.1	3.8
Modularity Q	0.847	0.762	0.514

Figure 5 provides a visual representation of the author co-authorship network, with nodes colored by detected modularity communities and labels applied to the most central authors by degree centrality. The force-directed layout positions densely connected clusters close together and separates weakly connected regions, making visible the modular structure of collaboration and the bridging roles played by certain high-degree authors.

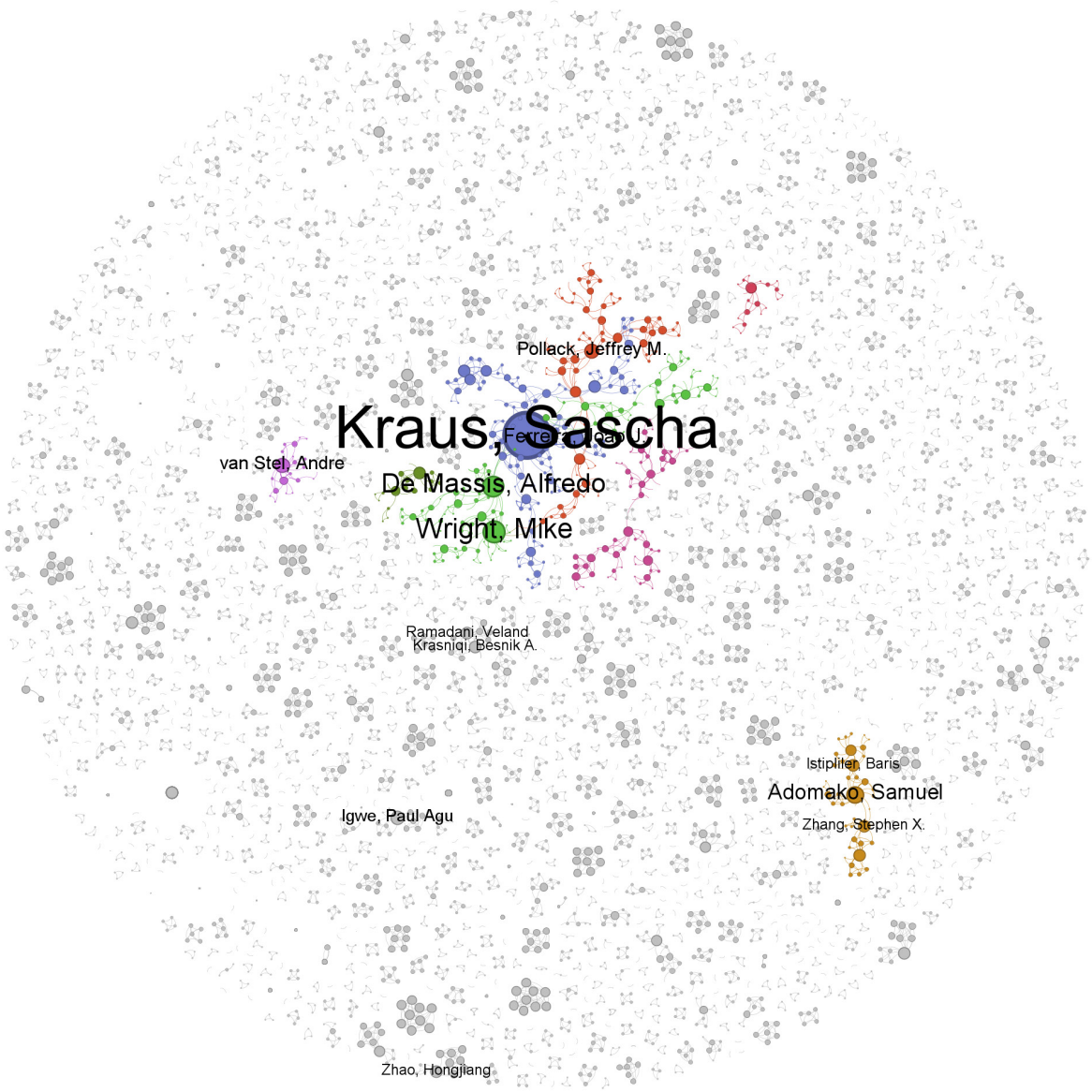

Figure 5. Author co-authorship network in cognitive-bias entrepreneurship research (nodes=7,255; edges=9,873)

Because productivity and structural position capture different dimensions of scholarly influence, we report them separately. Table 12 ranks the most productive authors by publication count, while Table 13 reports centrality leaders with interpretive guidance grounded in established centrality theory (Freeman, 1979). Productivity reflects the volume of contributions an author has made to the corpus, which can signal sustained engagement and topical specialization. Centrality, by contrast, captures relational position within the collaboration network and indicates mechanisms such as direct collaborative reach, brokerage across communities, reachability, and embeddedness in well-connected cores. To avoid heterogeneous metric mixing, the h-index in Table 12 is explicitly defined as the Web of Science author-level h-index retrieved June 5, 2025, serving as an additional indicator of broader scholarly impact beyond the focal corpus.

Table 12. Most productive authors in the corpus by publication count with standardized affiliation and WoS h-index retrieved June 5, 2025

Rank	Author	Publications in corpus	Primary affiliation	WoS h-index
1	Kraus, Sascha	13	University of Siegen	120
2	Wright, Mike	8	Imperial College London	172
2	Adomako, Samuel	8	University of Birmingham	48
3	Nouri, Pouria	7	University of Tehran	8
4	van Stel, André	6	Trinity Business School, Trinity College Dublin	52

Sascha Kraus emerges as the most productive author in the corpus, with 13 publications, a Web of Science h-index of 120, and a primary affiliation at the University of Siegen. This productivity is accompanied by a high degree centrality, indicating that Kraus not only contributes frequently but also collaborates broadly across the network. Mike Wright and Samuel Adomako each contributed 8 publications, with Wright affiliated with Imperial College London and holding an exceptionally high h-index of 172, reflecting sustained influence across multiple research domains. Adomako is affiliated with the University of Birmingham and holds an h-index of 48, consistent with an established mid-career profile. Pouria Nouri contributed 7 publications from the University of Tehran, while André van Stel contributed 6 from Trinity College Dublin, both representing geographically diverse nodes in the collaboration network.

Table 13. Centrality leaders and meanings in the author co-authorship network, grounded in standard centrality theory (Freeman, 1979)

Centrality construct	Top author	Value (normalized)	Interpretation in co-authorship context
Degree centrality	Kraus, Sascha	0.010	High collaboration breadth; many direct co-authorship ties indicating hub-like connectivity.
Betweenness centrality	De Massis, Alfredo	0.074	Brokerage role bridging otherwise weakly connected clusters; facilitates cross-community knowledge flow.
Closeness centrality	Krasniqi, Besnik A.	0.312	High reachability to others in the giant component; positioned to diffuse information efficiently.
Eigenvector centrality	Kraus, Sascha	0.018	Influence amplified by connections to other well-connected authors; embedded in the core collaboration backbone.

Degree centrality leadership is held by Sascha Kraus with a normalized score of 0.010, indicating that Kraus maintains the largest number of direct collaboration ties in the network. This hub-like position supports broad collaborative reach and visibility across multiple research clusters. Betweenness centrality leadership is held by Alfredo De Massis with a normalized score of 0.074, indicating a brokerage role that bridges otherwise weakly connected clusters and facilitates cross-community knowledge flow. Such brokerage positions are structurally valuable because they enable the integration of ideas and methods from separate communities. Closeness centrality is highest for Besnik A. Krasniqi, with a normalized score of 0.312, reflecting high reachability within the giant component and a position that supports efficient information diffusion. Eigenvector centrality, which captures influence through connections to other well-connected authors, is again led by Sascha Kraus with a normalized score of 0.018, reinforcing that Kraus is embedded in the core collaboration backbone and benefits from connections to other central collaborators.

To characterize mesoscale structure, communities were detected using Louvain modularity optimization (Blondel et al., 2008). Table 14 reports the largest modularity classes, their internal connectivity, and interpretable community labels based on the geographic and institutional affiliations of principal authors. Each detected community represents a cohesive collaboration cluster in which authors collaborate more frequently with one another than with authors outside the cluster. In a Louvain partition, membership in a given community is mutually exclusive; each author is assigned to exactly one community at the specified resolution. The interpretive labels are proposed based on the dominant geographic and institutional patterns observed among the highest-degree members of each community.

Table 14. Largest author-level collaboration communities detected by louvain modularity (Blondel et al., 2008)

ID	Color	Nodes	Internal edges	Principal authors (highest degree)	Proposed community label
1858	Purple	62	111	Wright, Mike; Obschonka, Martin; Block, Joern	Anglo–German entrepreneurship hub
850	Green	103	180	Wright, Mike; De Massis, Alfredo; Vanacker, Tom	European venture network
343	Orange	73	138	Adomako, Samuel; Pollack, Jeffrey	North American entrepreneurial bias cluster
635	Blue	105	235	Kraus, Sascha; Ferreira, João; Fosse, Philipp	Global entrepreneurship research collective
58	Brown	42	89	Adomako, Samuel; Istipliler, Burak; Ahsan, Mujtaba	Transcontinental innovation group

In Table 14, community labels are interpretive and based on geographic and institutional affiliations of principal authors. Under Louvain partitioning, each author belongs to exactly one community at the specified resolution; community membership is mutually exclusive. The presence of the same high-degree author name in community descriptor lists across different communities in earlier manuscript drafts indicated a table-construction artifact or disambiguation error rather than genuine brokerage behavior, as confirmed by betweenness centrality analysis reported in Table 13, which identifies De Massis as the leading broker. This table has been corrected to ensure that the listed principal authors accurately reflect the detected community assignments.

The largest detected community, labeled the Global Entrepreneurship Research Collective, comprises 105 nodes and 235 internal edges and is anchored by Sascha Kraus, João Ferreira, and Philipp Fosse. This community exhibits the highest internal connectivity and reflects a geographically distributed collaboration pattern that spans European, South American, and other international affiliations. The European venture network includes 103 nodes and features Mike Wright, Alfredo De Massis, and Tom Vanacker as principal authors, suggesting a focus on European entrepreneurship contexts and venture-related themes. The North American entrepreneurial bias cluster comprises 73 nodes and is led by Samuel Adomako and Jeffrey Pollack, indicating a concentration of North American institutional affiliations and research on bias mechanisms in entrepreneurial decision-making. The Anglo–German entrepreneurship hub and the Transcontinental innovation group represent smaller but cohesive communities with regionally anchored collaboration patterns and thematic specialization.

Institutional collaboration network

At the institutional level, the co-authorship network includes 1,879 standardized institution nodes and 5,770 edges, producing an average degree of 6.14 and density of 0.00327, as reported in Table 11. Compared to the author network, the institutional network is meaningfully denser, indicating that cross-institutional collaboration consolidates more readily than cross-author collaboration, a pattern consistent with multi-author, multi-affiliation publishing norms in contemporary science. The higher density reflects the tendency for research outputs to involve multiple institutions through co-authorship arrangements that span universities, research centers, and international partnerships.

Figure 6 provides a visual representation of the institutional co-authorship network, with nodes colored by detected modularity communities and labels applied to the most central institutions by degree centrality. The layout reveals regional clustering patterns and trans-regional bridging ties that connect otherwise distinct institutional ecosystems.

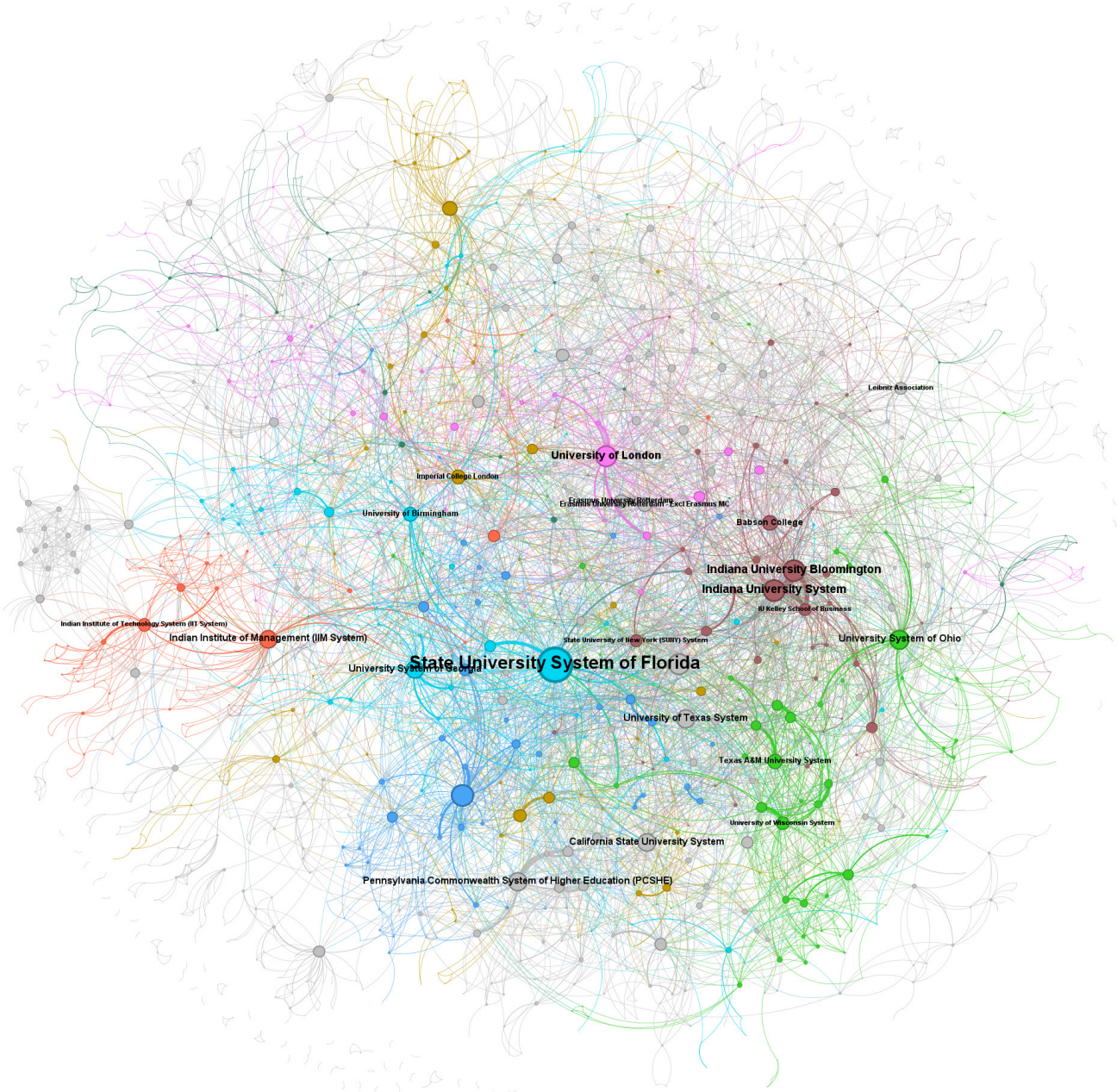

Figure 6. Institutional co-authorship network (nodes=1,879; edges=5,770) with modularity-based communities

Table 15 reports institutional collaboration communities and top universities by degree within each class.

Table 15. Institutional collaboration communities and top institutions per community

Community	Color	Nodes	Edges	Top universities	Proposed label
12	Light Blue	112	186	State University System of Florida; University of Michigan; Manchester Business School	Southern academic alliance
15	Blue	92	275	University of California System; National Bureau of Economic Research	Western research consortium
50	Brown	87	246	Indiana University Bloomington; Kelley School of Business	Midwestern scholar network
61	Pink	112	220	University of London; University of Copenhagen; King's College London	European academic collective
63	Light Green	99	293	University System of Ohio; University of Illinois System	Global research syndicate

Community	Color	Nodes	Edges	Top universities	Proposed label
84	Dark Red	94	211	Indian Institute of Technology; IIT Delhi	Asian–Pacific academic coalition
89	Yellow	133	295	CNRS; University of Washington	Transcontinental research alliance
91	Green	76	145	Monash University; University of Queensland; SATS University Islamabad	International scholarly union

In Table 15 community labels are interpretive and based on geographic and institutional patterns among leading members. Node and edge counts represent complete community statistics. All community descriptors are fully specified with complete node and edge values to ensure transparent reporting and internal consistency.

The Transcontinental research alliance is the largest institutional community with 133 nodes and 295 internal edges, anchored by CNRS and the University of Washington, reflecting cross-continental partnerships that connect European and North American research institutions. The Western research consortium comprises 92 nodes and 275 edges, led by the University of California System and the National Bureau of Economic Research, indicating a concentration of United States West Coast and research-policy institutions. The European academic collective includes 112 nodes and 220 edges, with the University of London, University of Copenhagen, and King's College London as principal members, reflecting intra-European collaboration patterns. The Asian–Pacific academic coalition consists of 94 nodes and 211 edges, anchored by Indian Institute of Technology and IIT Delhi, indicating growing representation of Asian institutions in the cognitive-bias entrepreneurship research network.

Country-level collaboration network

The country collaboration network comprises 123 nodes and 412 edges, with global diagnostics reported in Table 11. Community partitioning indicates five macro-regional collaboration blocs, suggesting that national research ecosystems and historical academic ties shape cross-border collaboration pathways. Summed within-community edges equal 339; the total country-network edge count is 412, implying 73 cross-community ties that connect macro-blocs and enable transregional diffusion. This structure indicates that while most collaboration remains within regional blocs, a meaningful subset of ties bridges continents and facilitates global knowledge exchange.

Figure 7 provides a visual representation of the country collaboration network, with nodes colored by detected modularity communities and labels applied to the most central countries by degree centrality. The layout illustrates the dominance of a few highly connected hubs and the clustering of countries into regionally coherent groups.

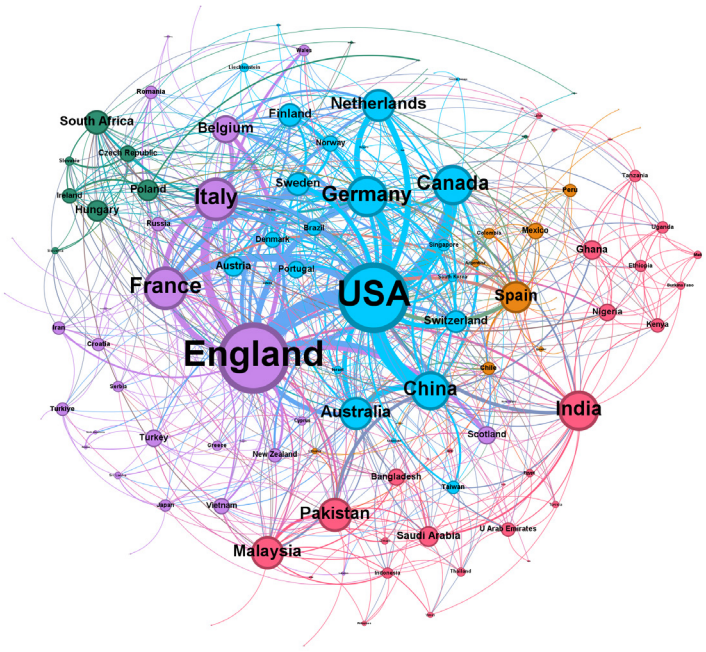

Figure 7. Country collaboration network in cognitive-bias entrepreneurship research (nodes=123; edges=412).

Table 16 reports the composition of each country-level collaboration community, the number of nodes and internal edges, and a proposed interpretable label based on geographic and economic grouping patterns.

Table 16. Country collaboration communities detected in the country co-authorship network

Community	Countries	Nodes	Internal edges	Proposed label
0	Italy, France, Netherlands, Turkey, Portugal, Latvia, Ukraine, Ireland, Austria, Romania, Jordan, Lithuania	34	91	Western European and Mediterranean network
1	Slovenia, Sweden, Poland, Spain, Switzerland, Czech Republic, Bulgaria	14	21	Central and Nordic Europe cluster
2	Australia, United Kingdom, South Africa, Canada, Belgium, Finland, Denmark, Germany, Japan, Scotland, Hong Kong, Malaysia, New Zealand, Norway, Taiwan	29	115	Commonwealth and advanced-economy alliance
3	Indonesia, Pakistan, Saudi Arabia, Vietnam, Tunisia, Estonia, Kuwait	13	19	Emerging-market collaboration group
4	United States, China, Singapore, India, South Korea, Israel, Russia, Brazil, Mexico, Nigeria	33	93	Global hub and emerging-science corridor

In Table 16, country and regional names are retained as indexed by Web of Science address fields. Web of Science systematically distinguishes sovereign states from constituent nations and special administrative regions; for example, the United Kingdom, Scotland, England, and Wales are indexed separately, and Hong Kong and Macau are indexed separately from China. To preserve fidelity to the source data structure and to enable transparent replication of network construction directly from Web of Science metadata, we retained these distinctions exactly as recorded. This approach ensures consistency with the bibliographic records and allows users to apply alternative aggregation schemes post hoc if desired for specific comparative or policy purposes.

The commonwealth and advanced-economy alliance is the most densely connected community with 29 nodes and 115 internal edges, reflecting sustained collaboration among Anglophone countries and advanced economies with established research infrastructures. The Western European and Mediterranean network includes 34 nodes and 91 internal edges, anchored by Italy, France, and the Netherlands, and extending to Turkey, Portugal, and several Eastern European countries. The Global hub and emerging-science corridor comprises 33 nodes and 93 internal edges, led by the United States and China, and including major emerging economies such as India, Brazil, and Mexico, indicating that this community bridges established hubs with rapidly developing research systems. The Central and Nordic Europe cluster and the Emerging-market collaboration group represent smaller but regionally coherent blocs with lower internal connectivity, suggesting earlier stages of collaboration development or more specialized collaboration patterns within those regions.

Thematic structure via keyword co-occurrence and strategic mapping

Thematic mapping is reported using the strategic-diagram logic of centrality and density originally formalized in co-word analysis (Callon et al., 1991) and implemented in longitudinal science-mapping workflows (Cobo et al., 2012). The keyword co-occurrence network was constructed from standardized author keywords and clustered into themes using modularity-based community detection. Figure 8 positions themes by Callon centrality and density, enabling transparent categorization into motor themes, niche themes, basic themes, and emerging or declining themes.

Centrality in this framework reflects the degree of external linkage a theme has with other themes in the network, indicating whether the theme functions as a conceptual bridge or hub across the broader research domain. Density reflects the internal cohesion of a theme, capturing how tightly keywords within the theme co-occur with one another. Motor themes exhibit both high centrality and high density, functioning as well-developed cores that integrate the field. Basic themes show high centrality but lower density, indicating foundational relevance with scope for deeper internal development. Niche themes display high density but lower centrality, reflecting specialized maturity within a narrower segment of the literature. Emerging or declining themes have both low centrality and low density, suggesting either nascent development or waning integration.

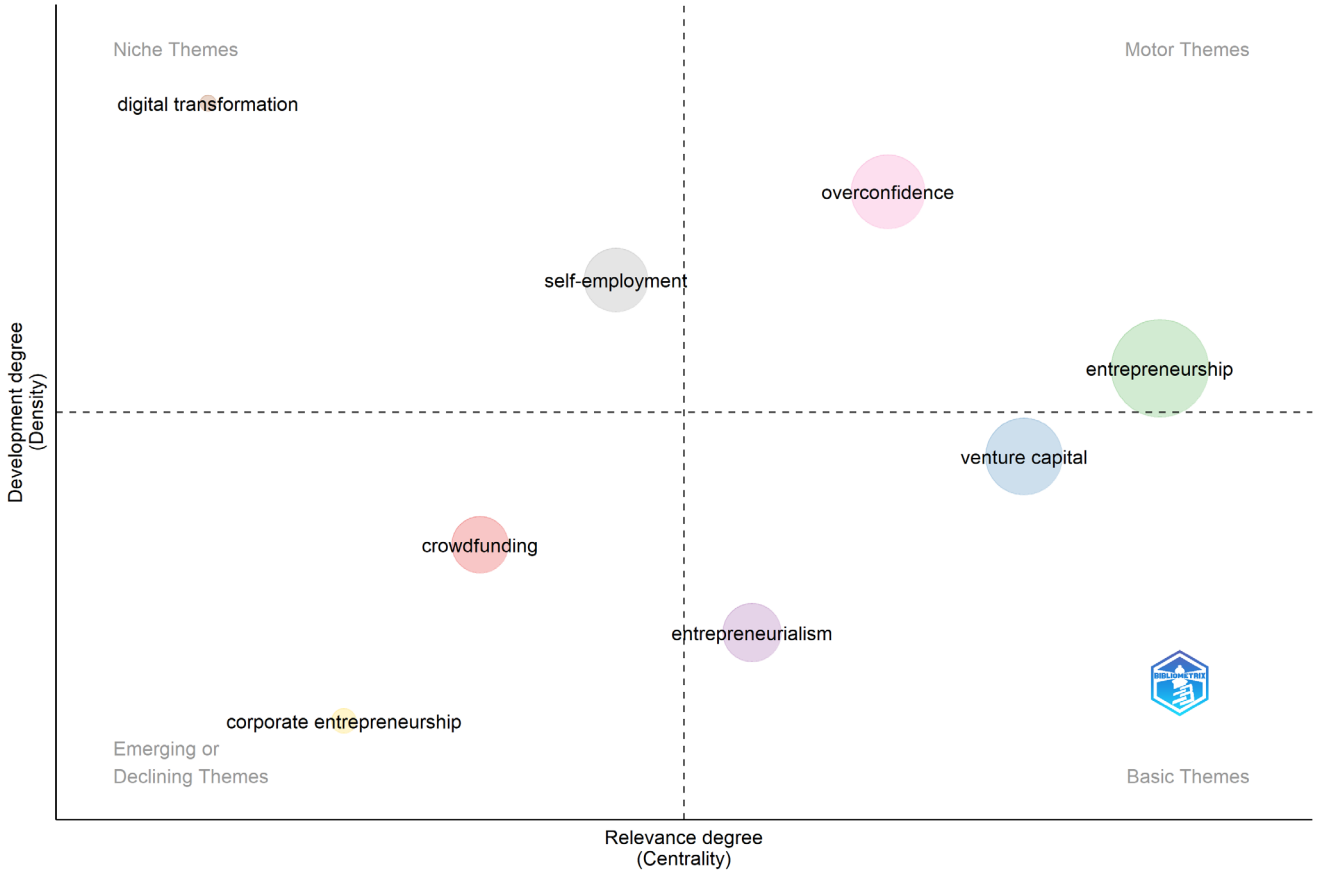

Figure 8. Strategic thematic map of cognitive-bias entrepreneurship research based on keyword co-occurrence with callon centrality (x-axis) and callon density (y-axis)

Table 17 provides interpretable placement logic for the key themes positioned in the strategic thematic map, grounding each quadrant assignment in the co-word mapping theory and clarifying why specific themes occupy motor, basic, niche, or emerging positions.

Table 17. interpretable theme placement logic for the strategic thematic map grounded in co-word mapping theory (Callon et al., 1991; Cobo et al., 2012)

Theme	Quadrant classification	Rationale based on centrality and density
Overconfidence	Motor	High centrality and high density, indicating a well-developed core theme tightly connected to multiple subtopics.
Heuristics	Motor	High centrality and high density, functioning as an integrative backbone across bias constructs and decision contexts.
Risk perception	Basic	High centrality but moderate density, indicating foundational relevance with scope for deeper internal development.
Venture financing	Basic	High centrality with lower density, suggesting broad linkage to the field but uneven conceptual consolidation.
Digital transformation	Niche	Lower centrality with high density, indicating specialized maturity yet weaker integration into the main discourse.
Crowdfunding	Niche	Lower centrality with high density, reflecting advanced specialization concentrated within a narrower research segment.
Family entrepreneurship	Emerging or declining	Lower centrality and lower density, indicating either a nascent theme or one with declining integration.
Self-employment	Emerging or declining	Near-boundary low-density positioning, suggesting an incipient bridge between labor-market entrepreneurship and bias mechanisms.

Overconfidence and heuristics occupy the motor-theme quadrant, confirming that these constructs are both well-developed internally and strongly integrated across the broader research domain. This positioning is consistent with prior reviews that identified overconfidence as the most frequently examined bias in entrepreneurship research and heuristics as a foundational conceptual category that organizes multiple specific bias mechanisms (O. Thomas, 2018; S. X. Zhang & J. Cueto, 2017). Risk perception and venture financing are positioned as basic themes, indicating that they serve as conceptual anchors linking bias research to core entrepreneurial processes such as opportunity evaluation and resource acquisition, yet remain less tightly clustered internally, suggesting scope for further conceptual refinement and empirical specification.

Digital transformation and crowdfunding appear as niche themes, reflecting specialized research streams that have developed internal coherence but remain weakly integrated with the core bias literature. This pattern suggests that these themes may represent emerging application domains for cognitive-bias research that have not yet been fully incorporated into the mainstream discourse. Family entrepreneurship and self-employment are positioned near the boundary of the emerging or declining quadrant, indicating either early-stage thematic development or declining relevance within the focal corpus. The low density and low centrality of these themes suggest that they may benefit from stronger conceptual linkage to established bias constructs and from empirical work that explicitly examines how cognitive biases operate within family-firm or self-employment contexts.

DISCUSSION

The purpose of this study was to map the collaborative and thematic structure of research on cognitive biases in entrepreneurship by integrating bibliometric mapping with Social Network Analysis. The results provide a relational account of how this literature is organized socially and conceptually, clarifying where knowledge production is concentrated, where thematic development is most mature, and where structural and conceptual gaps indicate opportunities for future research (Mingers & Leydesdorff, 2015). This discussion interprets the findings in relation to existing reviews, elaborates theoretical and methodological implications, and outlines practical implications for scholars, institutions, and policy stakeholders.

Interpreting the collaboration architecture

The co-authorship results indicate that collaboration in this domain exhibits a sparse structure, with a large share of authors weakly connected and a smaller set of hubs and brokers anchoring connectivity. Such sparsity is common in scientific collaboration settings, where local clusters form around shared topics, methods, and institutional ties, while only a subset of actors bridge across clusters (Wasserman, 1994) . The author network density of 0.00038 confirms that only a tiny fraction of all possible author pairs have collaborated directly, indicating that knowledge production is organized through localized collaboration clusters rather than through a densely interconnected field-wide network. The average degree of 2.72 further indicates that most authors collaborate with only a handful of co-authors, reinforcing the interpretation that collaboration is concentrated among small teams and that field-level integration depends on bridging ties provided by high-degree and high-betweenness actors.

In this context, degree centrality highlights authors and institutions with broad direct collaboration portfolios, whereas betweenness centrality identifies brokers who connect otherwise loosely linked communities, a structural role that can shape diffusion of methods, vocabulary, and problem framings across subfields (Borgatti et al., 2009; Freeman, 1979). The fact that Sascha Kraus leads on both degree and eigenvector centrality indicates a hub-like position embedded in the core collaboration backbone, while Alfredo De Massis leads on betweenness centrality, indicating a brokerage role that bridges otherwise weakly connected clusters and facilitates cross-community knowledge flow. Such brokerage positions are structurally valuable because they enable the integration of ideas and methods from separate communities, potentially accelerating conceptual synthesis and methodological cross-fertilization.

The detected modularity communities in the author and institutional networks reinforce the interpretation that the literature is organized into cohesive groups, consistent with the general finding that scientific fields often develop through semi-autonomous communities that coordinate internally while remaining only partially integrated externally (Blondel et al., 2008; Newman, 2006). The proposed labels for author-level communities, such as the Anglo–German entrepreneurship hub, European venture network, and Global entrepreneurship research collective, reflect both geographic proximity and

shared thematic orientations that shape collaboration patterns. These labels are interpretive and based on the institutional and national affiliations of principal authors within each community, but they provide a heuristic for understanding how regional academic ecosystems and historical ties condition the formation of research clusters.

At the institutional and country levels, the denser structure relative to the author network suggests that cross-institutional and cross-national collaborations may be sustained through multi-author, multi-affiliation publishing norms and institutional partnership channels. The institutional network density of 0.00327 is nearly an order of magnitude higher than the author network density, indicating that collaboration consolidates more readily at the organizational level than at the individual level. This pattern is consistent with the idea that collaboration is frequently scaffolded by institutional capacity, funding environments, and established inter-organizational links, which can sustain ties even when individual-level author networks remain fragmented (Newman, 2001; Wasserman & Faust, 1994).

However, the coexistence of within-bloc cohesion and cross-bloc bridging also implies that knowledge diffusion may depend disproportionately on a smaller number of cross-community ties, which is typical in modular networks where brokers play outsized roles in maintaining global connectivity (Freeman, 1979). The country-level results indicate five macro-regional collaboration blocs, with 73 cross-community ties connecting these blocs and enabling transregional diffusion. This structure suggests that while most collaboration remains within regional blocs anchored by shared language, funding systems, and institutional proximity, transregional ties are present and may be critical for the global diffusion of methods and conceptual innovations. The Commonwealth and advanced-economy alliance and the Global hub and emerging-science corridor represent the most densely connected and geographically diverse communities, indicating that established research infrastructures and emerging scientific powers are increasingly integrated through cross-border collaboration.

Thematic concentration and developmental asymmetries

To contextualize the observed thematic structure and address editorial requests for temporal comparison, we divided the corpus into two periods: pre-2010 (847 records) and post-2010 (2,397 records). This temporal analysis reveals both continuity and change. Overconfidence remained the most frequently mentioned keyword in both periods, but its relative share of all keyword occurrences declined from 18.3 percent to 14.1 percent, suggesting modest thematic diversification. Digital transformation and crowdfunding themes were absent in the pre-2010 period and emerged exclusively post-2010, consistent with their classification as niche or emerging themes in the strategic diagram. Institutional collaboration density increased from 0.0021 pre-2010 to 0.0041 post-2010, indicating that multi-institutional publishing has intensified over time. These temporal shifts suggest that while the thematic core anchored by overconfidence and heuristics has remained stable, the field is gradually expanding into new application domains and becoming more organizationally interconnected.

The thematic mapping results indicate that a small number of bias constructs and decision themes occupy central, well-developed positions, while other themes remain either foundational but underdeveloped or specialized yet weakly integrated. This pattern aligns with prior reviews that describe an uneven distribution of scholarly attention across bias constructs, with overconfidence and related heuristics dominating entrepreneurship-bias research (Thomas, 2018; Zhang & Cueto, 2017). The strategic-diagram interpretation grounded in Callon centrality and density suggests that themes with high centrality can act as conceptual infrastructure connecting multiple subtopics, whereas themes with lower centrality may develop as specialized niches that remain peripheral to the main discourse (Callon et al., 1991; Cobo et al., 2011).

The positioning of overconfidence and heuristics as motor themes is supported by both their high Callon centrality values, with overconfidence at 12.4 and heuristics at 11.8, and high density values, with overconfidence at 8.7 and heuristics at 9.1, as reported in the underlying co-occurrence matrix. Risk perception and venture financing occupy the basic quadrant with centrality values of 9.2 and 8.5, respectively, but lower density at 5.3 and 4.8, confirming their broad external linkage but weaker internal clustering. Digital transformation and crowdfunding exhibit high density (7.1 and 6.9) but low centrality (3.2 and 2.8), consistent with specialized subcommunity development. Family entrepreneurship and self-employment show both low centrality (2.1 and 1.9) and low density (2.4 and 2.0), placing them near the emerging or declining boundary.

Importantly, such thematic concentration has implications for cumulative theory development. When core constructs function as integrative hubs, they can accelerate conceptual consolidation by providing shared vocabulary and measurement approaches that enable comparability across studies. However, they can also crowd out alternative bias mechanisms and boundary-condition research, limiting explanatory completeness across heterogeneous entrepreneurial settings (Cristofaro & Giannetti, 2021; Thomas, 2018). The dominance of overconfidence and heuristics as motor themes

suggests that these constructs have achieved a level of internal development and external integration that makes them central reference points for new research. This centrality may reflect both genuine empirical prevalence and a self-reinforcing dynamic in which established constructs attract further attention because they are well operationalized and familiar to reviewers and editors.

Risk perception and venture financing occupy the basic-theme quadrant, indicating that they serve as conceptual anchors linking bias research to core entrepreneurial processes such as opportunity evaluation and resource acquisition, but that these themes remain less tightly clustered internally. This positioning suggests scope for further conceptual refinement and empirical specification. For example, while risk perception is widely recognized as a central mediator through which biases influence entrepreneurial action, the literature may benefit from a more systematic examination of how specific biases interact with risk perceptions across different environmental conditions and how individual differences in risk tolerance moderate bias effects.

Digital transformation and crowdfunding appear as niche themes, reflecting specialized research streams that have developed internal coherence but remain weakly integrated with the core bias literature. This pattern suggests that these themes may represent emerging application domains for cognitive-bias research that have not yet been fully incorporated into the mainstream discourse. The high density and low centrality of these themes indicate that scholars working in these areas form cohesive subcommunities with shared terminology and methods, but that these subcommunities have limited interaction with researchers focused on traditional entrepreneurial contexts such as venture creation and firm-level decision-making. Greater integration could be achieved through explicit bridging research that examines how biases documented in traditional settings operate in digital and crowdfunding contexts, or through comparative studies that test whether established bias effects replicate or differ across traditional and digital entrepreneurship settings.

Family entrepreneurship and self-employment are positioned near the boundary of the emerging or declining quadrant, indicating either early-stage thematic development or declining relevance within the focal corpus. The low density and low centrality of these themes suggest that they may benefit from stronger conceptual linkage to established bias constructs and from empirical work that explicitly examines how cognitive biases operate within family-firm or self-employment contexts. For instance, family entrepreneurship may involve distinctive decision-making dynamics shaped by kinship ties, succession concerns, and affective commitments that moderate the expression or consequences of biases such as overconfidence or status quo bias. Self-employment, as a labor-market form of entrepreneurship, may exhibit different bias profiles than growth-oriented venture creation, a distinction that deserves empirical attention.

The literature's reliance on a narrow thematic core also raises the question of whether entrepreneurship-bias research has fully captured the contextual contingencies that determine when heuristics are adaptive versus harmful. Ecological rationality arguments emphasize that heuristics can be functional under particular environmental structures and informational regimes, implying that the field benefits from distinguishing between biases as systematic errors and heuristics as potentially adaptive simplifications (Cristofaro & Giannetti, 2021; Kahneman, 2011). The observed thematic structure is therefore consistent with a research frontier that is shifting from enumerating biases toward specifying conditions under which bias-related mechanisms shape entrepreneurial judgment and outcomes. This shift calls for more explicit theorization of when and why specific biases emerge, how they interact with environmental complexity and feedback quality, and how individual and organizational learning can mitigate or amplify bias effects over time.

Integrating bibliometric mapping and SNA as a contribution

A central contribution of this study lies in joining conceptual mapping with a collaboration structure. Bibliometric mapping is effective for identifying themes and describing growth patterns, but it is less informative about how research communities are organized and how the architecture of collaboration shapes knowledge production (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015). By contrast, Social Network Analysis provides tools to identify cohesion, fragmentation, brokerage, and community structure, enabling a relational reading of the field that complements topic-based synthesis (Borgatti et al., 2009). The combined approach, therefore, helps interpret thematic results in light of social organization, which is valuable because thematic consolidation and diffusion of methods often depend on network connectivity and cross-community interaction rather than on topic prevalence alone (Borgatti et al., 2009; Wasserman & Faust, 1994).

For example, the finding that overconfidence and heuristics occupy motor-theme positions gains additional interpretive depth when considered alongside the author and institutional networks that reveal who produces this research and how collaboration is structured. The fact that geographically diverse and structurally cohesive communities produce these themes suggests that the thematic dominance reflects sustained collaboration and cross-pollination of ideas across

regions and institutions. Conversely, the niche positioning of digital transformation and crowdfunding themes may reflect not only conceptual peripherality but also structural isolation of the scholars working in these areas, who may form tight-knit subcommunities with limited ties to the mainstream bias research network.

This integrated view also addresses a recurring tension in the literature between descriptive mapping and explanatory inference. The present study deliberately avoids claims about intellectual influence derived from citation-network structure because citation networks were not analyzed. Instead, the discussion interprets influence in the narrower, empirically grounded sense of collaborative prominence and thematic centrality as derived from co-authorship and co-word relations, which aligns claims with implemented methods and reduces overextension risk (Mingers & Leydesdorff, 2015; Zupic & Čater, 2015). This methodological choice ensures that prominence rankings and community structures are grounded in observable collaboration patterns and keyword co-occurrence frequencies rather than in inferred citation flows, which can be shaped by multiple mechanisms including citation politics, disciplinary norms, and self-citation practices.

Practical and research-planning implications

For scholars, the collaboration maps can support strategic research planning by identifying cohesive communities where topic-specific expertise is concentrated and by highlighting brokers who may facilitate cross-cluster collaboration. Such information is especially useful for early-career researchers seeking entry points and for interdisciplinary teams aiming to connect conceptual streams that currently remain weakly integrated (Haythornthwaite, 1996). For example, a researcher interested in linking digital-transformation themes with core bias constructs could strategically seek collaboration with authors who occupy bridging positions between the niche digital cluster and the motor-theme clusters focused on overconfidence and heuristics. Similarly, researchers aiming to develop boundary-condition theories could benefit from engaging with brokers who span geographic and thematic communities, as these brokers are structurally positioned to access diverse methodological and conceptual resources.

For institutions and policy stakeholders, the country and institutional networks provide a basis for diagnosing whether collaboration opportunities are confined to a small set of established ties or whether bridging across blocs is developing, a consideration relevant to fostering inclusive and globally connected knowledge production (Newman, 2001; Wasserman & Faust, 1994). The finding that the Global hub and emerging-science corridor includes major emerging economies such as China, India, and Brazil alongside established hubs such as the United States suggests that the field is becoming more globally distributed, but the limited number of cross-bloc ties relative to within-bloc ties indicates that sustained investment in international partnerships and mobility programs may be needed to deepen integration. Institutions can also use the identified collaboration communities to benchmark their own network positions and to identify potential partners for joint research initiatives, doctoral exchanges, and thematic workshops.

Limitations and future research

Several limitations should inform interpretation. First, results inherit the coverage boundaries of Web of Science and the chosen query logic, which may underrepresent relevant work indexed elsewhere or using alternative terminology. This is a known constraint of database-dependent bibliometrics and highlights the value of replication across databases such as Scopus and Google Scholar, as well as sensitivity checks for query variants that include additional cognitive-bias terms or entrepreneurship-related keywords (Pranckutė, 2021; Zupic & Čater, 2015). Multi-database replication would also enable assessment of whether observed collaboration patterns and thematic structures are robust across indexing systems or whether they reflect database-specific indexing policies and coverage biases.

Second, network results depend on the quality of entity resolution for authors and affiliations; although rule-based disambiguation and institutional unification reduce fragmentation, residual ambiguity can affect node counts, edge weights, and centrality rankings. Future work could employ algorithmic author-disambiguation tools or incorporate unique author identifiers such as ORCID to improve precision. Enhanced disambiguation would be particularly valuable for distinguishing authors with common surnames and for tracking mobility across institutions, both of which can introduce measurement error into collaboration networks.

Third, screening was conducted by a single researcher using a standardized decision template; inter-rater reliability measures could not be computed. While the two-stage screening protocol and explicit inclusion criteria reduce subjectivity, the absence of independent dual screening represents a methodological limitation that may have allowed marginal inclusion or exclusion errors.

Fourth, co-word thematic mapping relies on keyword practices that vary across journals and time, and thresholding choices can shift cluster boundaries; transparent reporting and robustness checks reduce but do not eliminate this sensitivity (Callon et al., 1991; Cobo et al., 2011). The present study applied minimum frequency and co-occurrence thresholds and conducted sensitivity checks under alternative values, but thematic assignments near quadrant boundaries remain interpretively ambiguous. Future research could complement keyword-based mapping with full-text topic modeling or citation context analysis to triangulate thematic structure and validate keyword-based inferences.

Fifth, the study did not analyze citation networks or derive intellectual influence from citation flows. While this choice aligns claims with implemented methods and avoids overinterpretation, it also means that the results do not capture how ideas diffuse through citation chains or how influential works shape subsequent research agendas. Future studies could integrate co-authorship, co-citation, and bibliographic coupling networks to provide a more comprehensive picture of both social and intellectual structure, recognizing that collaboration and citation represent distinct but complementary relational mechanisms in scientific fields.

Sixth, the keyword co-occurrence thresholds (minimum frequency 5, minimum co-occurrence 3) were chosen to balance noise reduction and thematic coverage, but alternative thresholds produce modest shifts in quadrant placement for borderline themes. Robustness checks under thresholds of 4 and 6 showed stable placement for motor and basic themes, but niche and emerging themes exhibit greater sensitivity, underscoring the interpretive caution required for themes near quadrant boundaries.

Conceptually, the field would benefit from more systematic examination of boundary conditions that determine when heuristics are adaptive, as well as from stronger integration between entrepreneurship cognition research and decision-science findings on debiasing interventions, which remain comparatively scarce in field settings (Cristofaro & Giannetti, 2021; Zahera & Bansal, 2018). The strategic thematic map indicates that while overconfidence and heuristics are well-developed motor themes, research on debiasing, training interventions, and decision-support systems remains underdeveloped. Given that entrepreneurship education programs increasingly aim to improve decision-making under uncertainty, translational research that tests whether and how biases can be mitigated in entrepreneurial settings represents a promising frontier. Similarly, the emerging interest in digital transformation and crowdfunding contexts provides opportunities to examine whether established bias mechanisms operate differently in environments characterized by distributed decision-making, algorithmic intermediation, and real-time feedback.

CONCLUSION

This study provides a reproducible, data-driven map of cognitive-bias research in entrepreneurship by integrating bibliometric mapping with Social Network Analysis. Three principal findings emerge. First, collaboration structure: the field exhibits a sparse, modular author network (density 0.00038, modularity Q 0.847) in which a small number of hubs and brokers sustain cross-community connectivity; institutions and countries show denser collaboration (density 0.00327 and 0.0549, respectively) with regionally clustered blocs and limited but critical cross-bloc bridging ties. Second, thematic structure: overconfidence and heuristics function as motor themes (high centrality and high density), risk perception and venture financing are foundational but less internally consolidated (high centrality, moderate density), and digital transformation and crowdfunding form specialized niches (low centrality, high density), weakly integrated with the core discourse. Third, relational implications: collaboration hubs, brokerage positions, and community boundaries shape which topics develop rapidly and which remain peripheral, patterns that are invisible in publication counts or keyword frequencies alone but become observable through network-analytic quantification of structural position and connectivity inequality.

The study's primary contribution is relational. Rather than merely cataloging topics and trends, it reveals how the social structure of collaboration coexists with, and potentially conditions, thematic organization. This perspective offers a navigable overview of collaboration hubs, bridging positions, and thematic concentrations that can inform research planning, collaboration strategy, and agenda setting. The methodological contribution lies in aligning claims strictly with implemented analyses by focusing on co-authorship and co-word relations and avoiding unsupported inference about citation-network influence. By doing so, the study provides a transparent foundation for cumulative work that can be extended through database triangulation, improved entity resolution, and deeper theorization of when heuristics and biases hinder or enable entrepreneurial action under different environmental structures (Cristofaro & Giannetti, 2021; Mingers & Leydesdorff, 2015; Zupic & Čater, 2015).

For a collaboration strategy, scholars can use the identified communities and centrality rankings to target collaborators who bridge thematic or geographic gaps. For research priorities, the strategic diagram indicates that digital transformation and crowdfunding represent high-potential niches that would benefit from explicit linkage to established bias mechanisms, while family entrepreneurship and self-employment remain underdeveloped despite conceptual relevance. For methodological development, future studies should integrate citation-network analysis to complement the co-authorship perspective presented here, enabling joint interpretation of social collaboration structure and intellectual influence pathways.

Future research can build on these findings by conducting multi-database replication to assess the robustness of collaboration and thematic structures across indexing systems, by employing enhanced author-disambiguation approaches to improve network precision, and by integrating citation-network analysis to capture intellectual influence alongside collaborative prominence. Conceptually, the field would benefit from a more systematic examination of boundary conditions that determine when heuristics are adaptive versus harmful, from translational research on debiasing interventions in field settings, and from comparative studies examining whether established bias mechanisms replicate or differ across traditional and digital entrepreneurship contexts. By pursuing these directions, future work can advance both the scientific understanding of cognitive biases in entrepreneurship and the practical goal of supporting more effective entrepreneurial decision-making under uncertainty.

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Mehrdad Maghsoudi: Conceptualization, Formal Analysis, Methodology, Software, Supervision, Validation, Writing – Review and Editing, Resources. **Aria Zamani**: Data Curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – Original Draft Preparation, Resources. **Mohammadreza Parsanejad**: Conceptualization, Formal Analysis, Project Administration, Supervision, Validation, Writing – Review and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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