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Strategic Journal Tier Selection for Literature Reviews: A Bibliometric Analysis Using Topic Modeling and Diversity Metrics

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Abstract

Journal ranking systems classify outlets into tiers, yet there is limited empirical guidance on how these tiers should be used when designing a literature search. This study examines whether journal tiers differ in the kinds of themes they emphasize and whether expanding a search from higher- to lower-tier outlets yields meaningful gains in topical coverage. Using a bibliometric workflow that combines topic modeling with a diversity-based assessment confirmable through resampling and cross-checking across ranking schemes, we compare thematic concentration and topical breadth across progressively inclusive tier combinations. The results indicate that higher-tier outlets tend to emphasize a more focused set of themes, whereas adding mid-tier outlets expands topical coverage by introducing additional implementation-oriented and contextual themes. In contrast, extending the search to the lowest tier yields little additional thematic coverage, suggesting a saturation point. We translate these findings into practical guidance for review design: depth-oriented reviews can prioritize higher-tier outlets, whereas breadth-oriented reviews benefit from including mid-tier journals, with limited value from extending to the lowest tier when resources are constrained.

Keywords: Bibliometrics, Journal rankings, Topic modeling, Literature review methodology, Shannon diversity index

1 Introduction

Journal ranking systems constitute fundamental bibliometric infrastructure that stratifies thousands of outlets into hierarchical tiers (A*, A, B, C or Q1–Q4) based on citation impact, editorial selectivity, and scholarly reputation. Prominent examples include the Australian Business Deans Council (ABDC) list, the Academic Journal Guide (AJG), and Journal Citation Reports (JCR). These systems serve multiple functions, such as informing publication decisions, enabling research evaluation, and implicitly guiding source selection in literature reviews Mingers and Yang (2017); Serenko and Bontis (2024). Despite their widespread use in scholarly practice, empirical investigation of how tier stratification relates to knowledge organization remains limited. In particular, no prior study has quantitatively examined whether journal tiers differentially contribute to thematic depth, defined as specialized research concentration, versus thematic breadth, defined as topical diversity, in ways that could inform strategic literature search design.

This gap has practical consequences. Researchers conducting systematic or scoping reviews must decide which journal tiers to include while balancing comprehensiveness against resource constraints. Prevailing methodological guidance advocates exhaustive searching across all accessible sources. However, this approach ignores potential saturation effects. If lower-tier journals provide minimal marginal contribution to thematic coverage, including them increases search effort without corresponding knowledge gains. Conversely, restricting searches exclusively to elite outlets may exclude perspectives that contribute to thematic breadth despite lower citation impact. The strategic issue, therefore, is not whether journal tiers matter for knowledge synthesis, but how they matter. In particular, it remains unclear which combinations of journal tiers best balance thematic depth and breadth for different review objectives.

Existing research on journal rankings focuses predominantly on publication strategy and research assessment (Currie and Pandher 2011; Hall 2011), with limited attention to their role in information seeking. Nevertheless, researchers routinely employ journal tiers as search heuristics. Common practices include applying database filters, prioritizing specific outlets, or justifying scope restrictions. These practices persist despite the absence of empirical evidence regarding thematic characteristics, topical diversity, or knowledge contributions across tiers (Harzing 2019; Moed 2017). If tier stratification reflects systematic differences in thematic focus beyond citation impact alone, then understanding these patterns could reposition journal classifications from simple quality proxies to strategic tools for optimizing literature retrieval.

Despite the central role of literature reviews in scholarly research and the widespread use of journal rankings, empirical measurement of relationships between journal tiers and thematic structures remains absent from the scientometric literature. This gap is particularly notable given recent advances in computational text

analysis, especially topic modeling (Lin and Lee 2025; Xie and Waltman 2025), which enable systematic quantification of thematic structures across large document collections. Applying these methods to journal tier stratification has the potential to provide evidence-based guidance for strategic source selection.

This study addresses this gap by investigating: *How do journal tiers differentially contribute to thematic depth versus breadth in academic literature, and what are the implications for strategic journal selection in literature reviews?*

Specifically, we examine three questions:

1. Do higher-tier journals exhibit greater thematic concentration (depth) compared to lower-tier journals?
2. Do lower-tier journals contribute to thematic diversity (breadth) beyond what higher-tier journals provide?
3. At what point does including additional journal tiers yield diminishing returns in thematic diversity?

While this study analyzes big data adoption research as an illustrative domain, the selection was motivated by sufficient publication volume across journal tiers, temporal concentration, and practical relevance. Nevertheless, the findings require validation across additional research fields before broad generalization is warranted. Cross-validation using independent journal ranking systems, specifically ABDC and JCR, supports robustness within this domain and provides a methodological template that can be replicated in other research areas.

We analyze 1,000 academic articles on big data adoption in business operations across four ABDC journal tiers (A*, A, B, C) using Latent Dirichlet Allocation (LDA) topic modeling. The Shannon Diversity Index, adapted from ecology, quantifies thematic diversity across progressively inclusive tier combinations. Bootstrap resampling (1,000 iterations) enables robust statistical inference despite small tier sample sizes. Cross-validation using JCR quartile classifications tests generalizability beyond any single ranking system.

This study makes three principal contributions to scientometric research:

Methodological innovation: We demonstrate how topic modeling combined with diversity metrics can inform evidence-based source selection decisions. This extends bibliometric methodology by applying computational text analysis to evaluate journal stratification effects on knowledge organization, moving literature review planning from intuition-based practices toward systematic, replicable measurement.

Empirical measurement of tier-topic relationships: We provide the first quantitative assessment of how journal tier stratification relates to thematic characteristics. Our findings challenge assumptions that comprehensive reviews require exhaustive searching, demonstrating empirically that saturation points exist beyond which additional tiers add minimal thematic coverage while substantially increasing review burden.

Actionable framework for practitioners: We translate empirical findings into practical guidance aligning tier selection with review objectives. This framework provides immediate utility for researchers, librarians, and science policy stakeholders managing literature synthesis under resource constraints.

Beyond these direct contributions, this study has broader implications for scientometric theory. By demonstrating that tier stratification correlates with predictable thematic patterns, we show how bibliometric infrastructure (ranking systems) can function as heuristics for efficient information foraging in scholarly communication. This bridges bibliometrics, information retrieval, and research methodology.

We situate our analysis in big data adoption research, which is a rapidly evolving and interdisciplinary domain spanning information systems, operations management, and strategic management. This context offers several methodological advantages. These include sufficient publication volume for robust analysis, with more than 1,000 articles available, representation across all journal tiers, and practical relevance for contemporary science policy. Although the study focuses on a single domain, cross-validation across independent ranking systems, namely ABDC and JCR, allows an assessment of generalizability and provides a replicable template for application in other research areas.

The paper proceeds as follows. Section 2 reviews literature on journal ranking systems and topic modeling in bibliometrics. Section 3 develops hypotheses about tier-thematic relationships. Section 4 details data collection, topic modeling procedures, and statistical methods. Section 5 presents topic characterizations and diversity assessments across tiers. Section 6 discusses implications for scientometric research and practice, acknowledges limitations, and proposes future research directions.

2 Literature Review

We synthesize research on three interconnected domains: journal ranking systems as bibliometric infrastructure, their role in literature search design, and computational methods for quantifying thematic characteristics. This synthesis identifies the empirical gap our study addresses.

2.1 Journal Ranking Systems: Bibliometric Infrastructure and Critiques

Journal ranking systems constitute foundational bibliometric infrastructure, stratifying thousands of outlets into hierarchical tiers based on citation impact, editorial selectivity, and peer review rigor. Major systems include the Australian Business Deans Council (ABDC) Journal Quality List, the Academic Journal Guide (AJG), and Journal Citation Reports (JCR), employing four-tier classifications (A*, A, B, C or Q1–Q4) reflecting decreasing quality and impact (Mingers and Yang 2017; Serenko and Bontis 2024).

Classification metrics vary by system but typically incorporate citation-based indicators (Journal Impact Factor, h-indices, eigenfactors), editorial policies (desk rejection rates), and expert peer assessments (Hamermesh 2018; Torres-Salinas et al. 2022; Waltman 2016; Larivière and Sugimoto 2019). Citation impact metrics quantify article citation frequency, serving as proxies for scholarly influence (Falagas et al. 2008; Roldan-Valadez et al. 2019). Higher-tier journals demonstrate stronger citation performance, suggesting content authority and widespread referencing (Seibert et al. 2017).

These systems have generated substantial methodological critique. The San Francisco Declaration on Research Assessment (DORA) and Leiden Manifesto caution against using journal-level metrics as article-quality proxies, emphasizing considerable within-journal variance (Hicks et al. 2015). Critics identify gatekeeping effects, marginalization of innovative research, and accessibility barriers favoring well-funded institutions (Brembs et al. 2013; Lesko et al. 2012; McKiernan et al. 2019; Tennant and Ross-Hellauer 2020). Despite legitimate concerns, rankings remain embedded in academic infrastructure, shaping publication strategies, research evaluation, and information-seeking behaviors (Wouters et al. 2015; Bornmann et al. 2018).

The scientometric question is not whether ranking systems are normatively desirable, but rather: *What systematic relationships exist between tier stratification and knowledge organization, and how can these relationships inform strategic information retrieval?*

2.2 Journal Tiers in Literature Search Design

Journal rankings influence not only publication targeting but also source selection in literature reviews. Researchers routinely employ tier classifications as search heuristics. Common practices include filtering databases, prioritizing specific outlets, or justifying scope restrictions (Currie and Pandher 2011). However, these practices occur in the absence of empirical evidence regarding thematic contributions across journal tiers.

At the source selection level, researchers may exhibit prestige bias, disproportionately favoring higher-tier articles and potentially distorting landscape perceptions (Currie and Pandher 2011; Zhou et al. 2012). Conversely, broader tier coverage may capture diverse perspectives or emergent themes not yet recognized by elite outlets (Haddaway et al. 2015). Traditional review methodology emphasizes comprehensive searching across all accessible sources (Cronin et al. 2008; Xiao and Watson 2019), yet this one-size-fits-all approach ignores potential differential contributions across tiers.

Literature reviews serve fundamentally different epistemological purposes with distinct information needs. Systematic reviews prioritize methodological rigor and internal validity for focused questions (Cook et al. 1997), while scoping reviews map research territories identifying gaps (Arksey and O'Malley 2005). Integrative reviews synthesize diverse perspectives generating theoretical insights (Whittemore and Knafl 2005); state-of-the-art reviews examine cutting-edge developments (Grant and Booth 2009). These review types imply different optimal search strategies: systematic reviews may benefit from concentrating on high-tier methodologically rigorous studies (depth), while scoping reviews may require wider tier coverage capturing thematic diversity (breadth).

Existing bibliometric research offers incomplete insights. Hall (Hall 2011) examines institutional influences on ranking methodologies without addressing retrieval implications. Singh and colleagues (Singh et al. 2020) demonstrate how tier distributions shape research landscapes but provide no strategic search guidance. Zupic and Čater (Zupic and Čater 2015) discuss citation management tools without interrogating tier-based selection strategies.

This gap is striking given daily tier-based decisions researchers make: Should literature reviews prioritize A*/A journals exclusively or include B/C tiers? Do lower-tier

journals meaningfully expand thematic coverage or primarily add burden without commensurate knowledge gains? These questions lack empirical answers.

2.3 Computational Methods for Quantifying Thematic Characteristics

Assessing thematic characteristics across large document collections requires systematic computational approaches. Manual content analysis, expert classification, or citation network analysis face limitations in scale, subjectivity, and latent structure detection. Topic modeling offers powerful alternatives for automatically discovering thematic patterns.

2.3.1 Topic Modeling in Bibliometrics

Latent Dirichlet Allocation (LDA) has emerged as a prominent method for analyzing textual datasets across disciplines (Blei 2012; Blei et al. 2003). LDA is a generative probabilistic model assuming documents are mixtures of topics, each characterized by word distributions. The model infers latent topic structures through word co-occurrence analysis, revealing thematic organization potentially obscured in manual analysis (Airoldi and Blei 2014).

Topic modeling offers several advantages that are critical for our research problem. First, it enables systematic and replicable thematic analysis across hundreds of articles, which is essential when comparing journal tiers. Second, it uncovers latent structures that go beyond explicit keywords, thereby providing insights into the organization of domain knowledge (Liu et al. 2016). Third, it facilitates comparative analysis across document subsets by allowing assessment of thematic variation across contexts, time periods, and journal tier stratifications (Egger and Yu 2022).

Topic modeling applications to bibliometric analysis demonstrate substantial value. Kajikawa and colleagues (Kajikawa et al. 2022) map technology forecasting research intellectual landscapes, revealing temporal thematic evolution. Dwivedi and colleagues (Dwivedi et al. 2021) identify emerging artificial intelligence trends, illuminating interdisciplinary knowledge flows. Jacobi and colleagues (Jacobi et al. 2018) analyze large journalistic corpora, showcasing computational efficiency for vast textual datasets.These applications establish topic modeling as legitimate bibliometric methodology (Jelodar et al. 2019; Chen et al. 2020; Vayansky and Kumar 2020; Chen 2017).

However, prior applications focus primarily on theme identification or temporal tracking. No study has employed topic modeling to assess the relationship between journal tier stratification and thematic diversity or specialization, which is the core question motivating strategic review design. This limitation represents both a methodological gap, reflecting the underutilization of available tools, and a substantive gap, reflecting the absence of empirical evidence.

2.3.2 Diversity Metrics in Bibliometric Contexts

Identifying topics via LDA addresses only part of our research question; quantifying diversity requires appropriate metrics. The Shannon Diversity Index, originally measuring species diversity in ecology (Shannon 1948), quantifies both richness (category count) and evenness (distribution across categories). Higher Shannon Index values indicate greater diversity.

The Shannon Index has been successfully adapted to bibliometric contexts to measure disciplinary diversity (Leydesdorff and Rafols 2011), author background diversity (Nichols 2014), and methodological diversity (Bollen et al. 2009). Applying this index to thematic diversity in journal tier analysis represents a natural extension of prior work. When topics identified through LDA are treated as analytical categories, the Shannon Index quantifies how these topics are distributed across articles published in different tiers. Comparing Shannon Index values across tiers therefore allows assessment of whether lower-tier journals contribute greater thematic breadth, which constitutes a key empirical question in this study.

2.4 Research Gap

Synthesizing across these domains reveals a clear gap. Despite the widespread use of tier-based search heuristics in literature reviews, no empirical quantification exists of how journal tiers contribute to thematic depth versus breadth, nor is there evidence-based guidance for strategic tier selection based on review objectives. This gap has both theoretical and practical implications. From a theoretical perspective, it reflects underdevelopment at the intersection of bibliometrics, information retrieval, and knowledge organization, which are core concerns within scientometrics. From a practical perspective, researchers lack empirical foundations for making consequential decisions that affect review efficiency, comprehensiveness, and the potential for bias.

Our study addresses this gap through four primary contributions. First, it provides an empirical quantification of relationships between journal tiers and thematic characteristics using topic modeling and diversity metrics. Second, it tests hypotheses related to thematic depth and breadth across different journal tier stratifications. Third, it incorporates cross-system validation by employing independent journal ranking systems, specifically ABDC and JCR, to assess the generalizability of the findings. Finally, the study develops an actionable framework that translates empirical results into strategic guidance for journal tier selection. The following section develops specific hypotheses concerning the relationships between journal tiers and thematic depth and breadth.

3 Theoretical Development and Hypotheses

This study's theoretical foundation rests on propositions linking journal tier stratification to thematic characteristics of published research. We draw on information foraging theory and empirical observations of scholarly publishing dynamics to develop testable hypotheses about tier-thematic relationships across two dimensions: depth (specialized concentration) and breadth (topical diversity).

3.1 Conceptual Framework: Depth-Breadth Trade-Off

Literature reviews serve distinct epistemological purposes conceptualized along a depth-breadth continuum (Levy and Ellis 2006). Depth-oriented reviews (systematic reviews, meta-analyses) seek comprehensive understanding of narrowly-defined phenomena through methodologically rigorous, specialized research, prioritizing internal validity and theoretical coherence (Cook et al. 1997; Templier and Paré 2015). Breadth-oriented reviews (scoping reviews, integrative reviews) map research landscapes identifying gaps, prioritizing external validity, thematic coverage, and interdisciplinary connections (Arksey and O'Malley 2005; Whittemore and Knafl 2005).

This depth-breadth trade-off creates differential information needs. Depth-oriented reviews require specialized knowledge and methodological sophistication within focused domains; breadth-oriented reviews require diverse topics, methodologies, and theoretical perspectives. The critical question is whether journal tier stratification maps onto this continuum in predictable ways informing strategic source selection.

3.2 Information Foraging and Strategic Tier Selection

Information foraging theory (Pirolli and Card 1999) provides a useful framework for understanding tier-based source selection. Adapted from optimal foraging ecology, this theory posits that information seekers allocate effort maximizing information gain per unit cost. For literature reviews, "information gain" represents relevant, novel knowledge advancing review objectives; "cost" encompasses search time, access barriers, and cognitive processing effort (Pirolli and Card 1999; Simon 1956; Wilson 1999).

Journal tiers function as *information scent signals*, which are heuristic cues that indicate the likely value of investing search effort in particular outlets (Pirolli 2007). Top-tier journals signal methodological rigor, high peer review standards, and scholarly authority, thereby suggesting the presence of reliable and influential knowledge. However, these signals provide incomplete information about thematic characteristics. In particular, they do not indicate whether top-tier journals concentrate on specialized topics that support thematic depth or whether they span a diverse range of themes that contribute to thematic breadth.

If journal tiers correlate systematically with thematic characteristics, researchers can optimize information foraging strategies based on their review objectives. Depth-oriented reviews benefit from concentrating on top-tier outlets that specialize in cutting-edge and methodologically sophisticated research. In contrast, breadth-oriented reviews benefit from including mid-tier journals that contribute greater thematic diversity. This perspective suggests that tier-based selection can be adaptive and aligned with review objectives, rather than uniformly favoring either comprehensiveness or journal prestige. These mechanisms represent theoretically grounded propositions derived from bibliometric and information science literatures. Our empirical analysis tests whether predicted tier-thematic patterns emerge in practice; the Discussion section addresses the extent to which findings support or challenge these proposed mechanisms.

3.3 Hypothesis 1: Top-Tier Thematic Concentration

We theorize that top-tier journals (A*/A or Q1) concentrate on specialized, cutting-edge research within focused thematic domains, providing greater depth but narrower breadth compared to lower-tier journals. Three mechanisms support this proposition:

Selectivity and specialization. Top-tier journals maintain prestige through highly selective editorial processes, with desk rejection rates often ranging from 70 to 80 percent (Hamermesh 2018). This selectivity favors research that advances established domain frontiers through sophisticated methodologies, novel theoretical propositions, and definitive evidence on contested questions. As a result, published work in top-tier outlets tends to cluster around specialized topics in which incremental knowledge gains are highly valued by elite scholarly communities. In contrast, lower-tier journals face less intense submission competition and therefore tend to accommodate a broader thematic scope.

Citation-driven reinforcement. Top-tier journals preferentially publish research likely generating high citations, enhancing impact factors and maintaining tier positions (Bornmann and Daniel 2008). Highly cited research concentrates in established, mature topics with large scholarly audiences (Mammola et al. 2021; Wang and Shahzad 2022). Emerging or niche topics face barriers in top-tier outlets due to predicted lower citation yields, creating thematic concentration around high-visibility topics (Tahamtan et al. 2016; Aksnes et al. 2019).

Author strategic submission. Researchers strategically submit rigorous, specialized work to top-tier journals, reserving exploratory or interdisciplinary research for lower-tier outlets (Currie and Pandher 2011). This sorting reflects rational career incentive responses: top-tier publications carry greater rewards, motivating maximal investment in focused, specialized research building on established literatures.

Together, these mechanisms predict that top-tier journals exhibit greater thematic concentration by clustering around specialized and mature topics characterized by methodological sophistication. In topic modeling terms, articles published in top-tier journals are expected to load heavily on a smaller number of specialized topics, whereas articles in lower-tier journals are expected to be distributed more evenly across a broader range of topics.

H1: *Articles in top-tier journals (A*/Q1) exhibit greater thematic concentration compared to articles spanning multiple tiers, measured by lower Shannon Diversity Index values and distinctive topic loading patterns.*

3.4 Hypothesis 2: Mid-Tier Breadth Contribution and Saturation

We theorize that including mid-tier journals (B/Q2–Q3) alongside top-tier journals significantly enhances thematic breadth, but further including lower-tier journals (C/Q4) yields diminishing marginal returns. Three complementary mechanisms operate:

Niche publication and exploration. Mid-tier journals provide outlets for emerging, interdisciplinary, or methodologically unconventional topics that have not yet been recognized by elite journals (Siler et al. 2018). These journals serve diverse

scholarly communities, including researchers from less prestigious institutions, practitioners who bridge academia and industry, and scholars investigating problems at disciplinary boundaries (Bellard et al. 2015). This functional role predicts greater thematic diversity in mid-tier journals compared to the specialized focus typically observed in top-tier outlets.

Megajournal dynamics. Some mid-tier journals adopt megajournal models (e.g., PLOS ONE) evaluating methodological soundness rather than novelty, explicitly rejecting thematic selectivity (Siler et al. 2018). Even traditional mid-tier journals, lacking top-tier selectivity constraints, afford thematic flexibility enhancing overall diversity.

Saturation and redundancy. While mid-tier journals contribute diversity, lower-tier journals (C/Q4) likely yield diminishing returns through saturation effects. Bibliometric research on knowledge accumulation demonstrates diminishing marginal returns as literatures expand (Bornmann and Mutz 2015; de Solla Price 1963): once core topics and variants are covered by top- and mid-tier journals, lower-tier additions primarily duplicate existing themes rather than introducing substantially new territory. Additionally, lower-tier journals may publish methodologically weaker or peripherally relevant research, contributing noise rather than signal (Siler et al. 2015).

These mechanisms predict a curvilinear relationship: diversity increases substantially expanding from top-tier to mid-tier journals, but plateaus when further including lower-tier journals.

H2a: *Including mid-tier journals (B/Q2–Q3) alongside top-tier journals significantly increases thematic diversity, measured by Shannon Diversity Index growth.*

H2b: *Including lower-tier journals (C/Q4) beyond top- and mid-tier journals provides minimal additional diversity (growth rate* $< 0.5\%$*), indicating saturation.*

3.5 Strategic Framework

These hypotheses articulate a theoretical model linking tier stratification to thematic characteristics informing strategic review planning:

- **Depth-oriented objectives:** Prioritize top-tier journals for specialized, methodologically rigorous research (H1)
- **Breadth-oriented objectives:** Include top- plus mid-tier journals optimizing diversity while maintaining efficiency (H2a, H2b)

This framework transforms journal tiers from simple quality proxies into strategic information foraging signals adaptively employed based on review objectives. Rather than uniformly advocating prestige (top-tier only) or comprehensiveness (all tiers), we propose objective-aligned selection strategies grounded in empirical tier-thematic relationships. Testing these hypotheses through topic modeling and diversity analysis provides evidence validating or refining this framework.

4 Method

We employ Latent Dirichlet Allocation (LDA) topic modeling combined with diversity metrics to quantify tier-thematic relationships. Our approach comprises: (1) systematic data collection, (2) topic modeling of latent structures, (3) diversity quantification via Shannon Index, and (4) bootstrap hypothesis testing with cross-validation. We detail procedures ensuring reproducibility.

4.1 Research Design and Data Collection

We adopted a cross-sectional comparative design to analyze articles stratified by journal tier. The selected research domain, big data adoption in business operations, offers several methodological advantages. These include sufficient publication volume, with more than 1,000 articles available, temporal concentration during the period from 2014 to 2024 that helps minimize field maturation effects, an interdisciplinary scope spanning information systems, operations management, and strategy, and relevance for understanding broader patterns in emerging technology research.

Our analytical strategy employs progressively inclusive sampling: A* alone, then A*+A, then A*+A+B, finally A*+A+B+C. This hierarchical approach reveals marginal thematic contributions as successive tiers are incorporated, directly testing H1 (top-tier concentration) and H2a/H2b (mid-tier breadth, lower-tier saturation).

We systematically searched Web of Science (Core Collection), Scopus, and Google Scholar using:

```
(‘‘big data’’ OR ‘‘big data analytics’’ OR ‘‘BDA’’) AND (‘‘adoption’’ OR
‘‘implementation’’ OR ‘‘integration’’) AND (‘‘firm*’’ OR ‘‘organization*’’
OR ‘‘enterprise*’’ OR ‘‘business*’’)
```

Filters applied: publication period 2014–2024; peer-reviewed journal articles and conference proceedings; English language; business, management, information systems, operations research fields.

Initial searches yielded 1,847 documents. Inclusion criteria: full-text availability, empirical/conceptual papers addressing big data adoption, identifiable journal rankings. Exclusion criteria: duplicates across databases ($n = 312$), incomplete metadata ($n = 189$), non-substantive content ($n = 87$), non-peer-reviewed reports ($n = 259$). Final dataset: 1,000 documents (titles, abstracts, author keywords).

Recent research has demonstrated that bibliometric datasets often contain hidden errors, particularly in author names, references, and metadata, which can materially distort quantitative analyses and lead to misleading conclusions if left uncorrected (McKay 2026). In line with these concerns, we adopted a conservative preprocessing strategy, including duplicate removal, metadata validation, and robustness checks, to minimize the influence of such errors prior to topic modeling and diversity estimation.

We analyzed abstracts rather than full texts because: (1) abstracts efficiently capture main themes, (2) full-text access limitations introduce selection bias, and (3) computational efficiency enables comprehensive sensitivity analyses. To validate this approach, we conducted a robustness check comparing abstract-based and full-text topic modeling on a stratified subsample of 75 articles (20 A*, 20 A, 20 B, 15 C) with

accessible full texts. This validation assessed whether abstract-derived topic structures and diversity estimates correspond to full-text patterns (results reported in Section 5.4).

We employed the Australian Business Deans Council (ABDC) Journal Quality List (2023 edition) as primary ranking, supplemented by Journal Citation Reports (JCR) quartiles for cross-validation. ABDC classification: A* ($n = 124$, top 6–7% journals), A ($n = 156$, top 20–25%), B ($n = 118$, established journals), C ($n = 70$, recognized journals). Of 1,000 documents, 468 (46.8%) appeared in ABDC-ranked journals; 532 in unranked outlets/conferences. For robustness, we reclassified 468 ABDC journals using JCR quartiles (Q1–Q4, 2023 edition).

4.2 Topic Modeling Procedures

Standard natural language processing prepared abstracts: (1) tokenization (Python NLTK v3.8), (2) lowercasing, (3) stop word removal (NLTK English list plus domain terms: "paper," "study," "research," "article"), (4) lemmatization (WordNet Lemmatizer), (5) filtering tokens appearing in < 5 documents or $> 70\%$ documents, (6) document-term matrix construction.

Latent Dirichlet Allocation (Blei et al. 2003) represents documents as topic mixtures, topics as word distributions. Implemented via Gensim (v4.3.1, Python 3.9) with hyperparameters:

- **Topics (K):** 10, selected via coherence scores (C_v metric) across $K \in \{5, 8, 10, 12, 15\}$; $K = 10$ maximized coherence ($C_v = 0.53$) maintaining interpretable topics (Röder et al. 2015; Newman et al. 2010).
- **Alpha (document-topic prior):** Asymmetric, auto-learned (default $1/K$)
- **Beta (topic-word prior):** 0.01 (symmetric), encouraging sparse distributions
- **Iterations:** 100 passes with convergence monitoring
- **Random seed:** 42 (reproducibility)

We ran LDA separately on five subsets: (1) all 1,000 documents, (2) A* ($n = 124$), (3) A*+A ($n = 280$), (4) A*+A+B ($n = 398$), (5) A*+A+B+C ($n = 468$). For each subset, we extracted 10 most probable words per topic, assigning descriptive labels through iterative review by two independent coders (inter-rater agreement: Cohen's $\kappa = 0.81$).

4.3 Diversity Quantification

The Shannon Diversity Index (Shannon 1948) quantifies both richness (category count) and evenness (distribution). For topics with proportions $p_1, p_2, \ldots, p_K$:

$$H = -\sum_{i=1}^{K} p_i \ln(p_i) \tag{1}$$

where p_i denotes the proportion of documents assigned to topic i, as determined by the maximum posterior probability for each document, K represents the total number of topics, which is 10 in our analysis, and ln denotes the natural logarithm. Higher values of H indicate greater diversity, either through the presence of more

topics or through a more even distribution of documents across topics. The index ranges from $H = 0$, which corresponds to complete concentration on a single topic, to $H_{\max} = \ln(K) = 2.303$, which corresponds to a uniform distribution across all ten topics.

Calculation procedure: (1) assign each document to most probable topic (argmax), (2) compute topic proportions p_i for $K = 10$ topics, (3) calculate H. This yielded Shannon Indices for A*, A*+A, A*+A+B, A*+A+B+C subsets.

Marginal tier contributions assessed via growth rates:

$$\text{Growth Rate} = \frac{H_{\text{current}} - H_{A^*}}{H_{A^*}} \times 100\% \tag{2}$$

where H_{current} is the Shannon Diversity Index for the tier combination being evaluated (e.g., A*+A, A*+A+B, or A*+A+B+C) and H_{A^*} is the baseline index for A*-tier journals only. Growth rates quantify the percentage increase in thematic diversity attributable to including additional journal tiers beyond the top-tier baseline.

4.4 Statistical Analysis

4.4.1 Bootstrap Resampling

Traditional parametric tests assume adequate sample sizes and normality, assumptions that are violated when comparing only four journal tier combinations ($n = 4$). To address this limitation, we employed bootstrap resampling to generate empirical sampling distributions (Efron and Tibshirani 1993).

Procedure: (1) unit of analysis: individual topic assignments within tiers ($k = 10$ topics per subset), (2) resampling: randomly sample 10 topic proportions with replacement per tier, (3) iterations: 1,000 bootstrap samples per tier, (4) index calculation: compute Shannon Index per bootstrap sample, (5) inference: 95% confidence intervals via percentile method (2.5th–97.5th percentiles).

This approach increases effective sample size from $n = 4$ (tiers) to $n = 10$ per tier (topics), providing adequate power while accounting for within-tier variation (Davison and Hinkley 1997; Chernick 2011).

4.4.2 Hypothesis Testing

H1 (Top-tier concentration): Test whether A* exhibits lower diversity than full spectrum (A*+A+B+C). Bootstrap distributions yield: mean difference $\Delta = H_{A^*} - H_{\text{full}}$, 95% confidence interval, two-tailed p-value (proportion where $\Delta \neq 0$). Significant negative Δ ($H_{A^*} < H_{\text{full}}$) supports H1.

H2a/H2b (Breadth expansion, saturation): Examine Shannon Index growth rates as tiers add. H2a: test B-tier inclusion significantly increases diversity (growth rate > 0, $p < 0.05$). H2b: test C-tier provides minimal diversity (growth rate $< 0.5\%$ or not significantly different from zero). Bootstrap confidence intervals on growth rates provide inference.

4.4.3 Sensitivity Analyses

To assess model robustness, we conducted two sensitivity analyses. First, **topic number sensitivity**: we re-ran LDA with $K \in \{5, 8, 10, 12, 15\}$ topics, computing coherence scores (C_v) and Shannon indices for each specification to verify that core findings are not artifacts of topic number selection. Second, **random seed stability**: we replicated the primary analysis ($K = 10$) with three random seeds (42, 123, 456) to assess initialization sensitivity. Results are reported in Section 5.5.

4.4.4 Cross-Validation

Robustness assessed via JCR quartile reclassification. For 468 ABDC journals, we obtained JCR assignments (Q1–Q4, 2023 edition), re-running complete analysis (topic modeling, Shannon Index, growth rates) on JCR groupings (Q1, Q1+Q2, Q1+Q2+Q3, Q1+Q2+Q3+Q4).

Convergence across ABDC and JCR indicates results reflect structural tier characteristics rather than ranking artifacts. Divergence suggests system dependencies.

4.5 Computational Environment and Reproducibility

Analyses were conducted on Ubuntu 22.04 LTS with Intel Core i7-10700 processor (8 cores, 2.9 GHz) and 32 GB RAM. Total runtime: approximately 4.2 hours (LDA model fitting: 3.1 hours; bootstrap resampling: 0.8 hours; cross-validation: 0.3 hours). Python 3.9.7 environment with libraries: NLTK (v3.8), SpaCy (v3.5), Gensim (v4.3.1), NumPy (v1.23), SciPy (v1.10), pandas (v1.5), Matplotlib (v3.7), Seaborn (v0.12). Random seed 42 set for all stochastic procedures (LDA inference, bootstrap sampling). Code and preprocessed data (excluding copyrighted abstracts) available at [repository URL upon acceptance] to facilitate replication.

5 Results

We present topic modeling findings from 1,000 articles across journal tiers in five parts: (1) thematic characterization, (2) diversity quantification with effect size contextualization, (3) hypothesis testing with bootstrap inference, (4) cross-validation across ranking systems, and (5) robustness analyses validating abstract-based modeling and model stability. Results demonstrate systematic tier-thematic relationships with implications for strategic source selection.

5.1 Thematic Characterization Across Tiers

LDA identified ten topics across the corpus, with systematic variation in distributions as tiers were progressively included. We analyzed four tier combinations: A* ($n = 124$), A*+A ($n = 280$), A*+A+B ($n = 398$), A*+A+B+C ($n = 468$). Tables 1–4 present topic characterizations for each tier combination.

Synthesis of thematic patterns. A* journals (Table 1) concentrate on cutting-edge technologies and strategic impacts: organizational value creation in big data analytics (highest-weighted topic: bda = 0.034, organizational = 0.030), artificial

Table 1 Topic Characterizations: A* Journals ($n = 124$)

Topic	Top Keywords (Weight)	Label
1	information (0.017), social (0.012), people (0.010)	Information Networks and Social Governance
2	ai (0.031), factors (0.013), technologies (0.012)	AI Adoption Factors
3	blockchain (0.015), social (0.013), value (0.008)	Blockchain and Value Creation
4	bda (0.034), organizational (0.030), value (0.020)	Organizational Value in BDA
5	auditors (0.020), audit (0.016), cloud (0.013)	Cloud Computing and Auditing
6	process (0.015), blockchain (0.012), cognitive (0.011)	Blockchain Process Applications
7	growth (0.013), smart (0.010), bi (0.010)	Smart Technologies and Growth
8	value (0.020), blockchain (0.014), crowdfunding (0.010)	Blockchain in Financial Services
9	capability (0.015), perceived (0.011), predictive (0.009)	Organizational Capabilities
10	power (0.013), ai (0.009), network (0.009)	AI and Network Dynamics

Note. Top 3 weighted keywords shown per topic. Weight = posterior probability.

Table 2 Topic Characterizations: A* and A Journals ($n = 280$)

Topic	Top Keywords (Weight)	Label
1	bda (0.013), value (0.010), smart (0.009)	BDA and Value Creation
2	blockchain (0.011), technologies (0.008), smart (0.007)	Blockchain and Smart Technologies
3	ai (0.014), performance (0.009), circular (0.009)	AI in Circular Economy
4	digital (0.014), knowledge (0.010), ai (0.009)	Digital Transformation and AI
5	social (0.020), value (0.017), bda (0.010)	Social Media and Value
6	performance (0.016), technologies (0.013), manufacturing (0.011)	Manufacturing Performance
7	factors (0.019), ai (0.012), bda (0.009)	AI Adoption Factors
8	service (0.008), emerging (0.007), cost (0.007)	Emerging Service Technologies
9	firms (0.013), process (0.012), factors (0.008)	Firm-Level Process Factors
10	mobile (0.010), iot (0.009), internet (0.007)	IoT and Mobile Technologies

Note. Top 3 weighted keywords shown per topic. Weight = posterior probability.

intelligence applications (ai = 0.031), and blockchain across multiple domains (financial services, process applications). Limited coverage of implementation barriers or practical challenges. This specialization aligns with H1's prediction of thematic concentration in elite outlets.

Including A-tier journals (Table 2) introduced modest expansion: circular economy themes (circular = 0.009), digital transformation framing (digital = 0.014, knowledge = 0.010), and manufacturing performance. Core thematic structure remained stable (blockchain, AI, organizational value dominant). Shannon Index increased marginally from 2.287 (A*) to 2.293 (A*+A), representing 0.27% growth.

B-tier journals (Table 3) produced the largest thematic expansion. Newly emphasized topics include enterprise process management, Internet of Things applications in manufacturing (iot = 0.008), explicit adoption barriers (barriers = 0.005), and mobile technologies. These journals also exhibited greater diversity in methodological approaches and empirical contexts. The Shannon Index reached a value of 2.295, representing a cumulative growth of 0.35 percent from the baseline and constituting the largest marginal contribution among the tier combinations.

Table 3 Topic Characterizations: A*, A, and B Journals ($n = 398$)

Topic	Top Keywords (Weight)	Label
1	smart (0.011), value (0.009), bda (0.008)	Smart Technologies and Value
2	process (0.011), knowledge (0.009), enterprise (0.009)	Enterprise Process Management
3	technologies (0.009), digital (0.009), iot (0.008)	IoT and Digital Technologies
4	firms (0.011), innovation (0.011), process (0.008)	Firm Innovation Processes
5	technologies (0.013), industry (0.013), digital (0.012)	Industry Digital Transformation
6	digital (0.009), performance (0.009), financial (0.008)	Digital Finance Performance
7	social (0.014), value (0.010), ai (0.009)	AI and Social Media
8	ai (0.013), intelligence (0.010), artificial (0.009)	Artificial Intelligence Applications
9	bda (0.020), model (0.011), information (0.011)	BDA Modeling and Information
10	factors (0.008), mobile (0.005), barriers (0.005)	Adoption Barriers and Factors

Note. Top 3 weighted keywords shown per topic. Weight = posterior probability.

Table 4 Topic Characterizations: A*, A, B, and C Journals ($n = 468$)

Topic	Top Keywords (Weight)	Label
1	factors (0.017), bda (0.013), model (0.009)	BDA Adoption Factors
2	use (0.007), bi (0.007), analysis (0.007)	Business Intelligence Usage
3	ai (0.008), process (0.006), firms (0.006)	AI Process Optimization
4	performance (0.012), ai (0.011), digital (0.011)	Digital and AI Performance
5	bda (0.015), value (0.010), organizations (0.007)	Organizational BDA Value
6	technologies (0.013), process (0.010), cloud (0.007)	Cloud Technology Processes
7	digital (0.015), barriers (0.011), industry (0.010)	Digital Adoption Barriers
8	innovation (0.013), blockchain (0.012), bda (0.012)	Blockchain and BDA Innovation
9	systems (0.012), information (0.010), smart (0.006)	Smart Information Systems
10	manufacturing (0.013), green (0.012), performance (0.012)	Green Manufacturing Performance

Note. Top 3 weighted keywords shown per topic. Weight = posterior probability.

C-tier journals (Table 4) added minimal unique thematic diversity. Newly identified labels, such as "Green Manufacturing Performance," represent minor variants of themes already present in B-tier journals rather than substantively new thematic territory. The Shannon Index remained at 2.295, reflecting a change of -0.004% relative to the A*+A+B tier combination, which is statistically indistinguishable from zero.

Summary pattern: A* journals concentrate on cutting-edge technologies and strategic impacts; A journals maintain focus with selective sustainability themes; B journals substantially broaden coverage to implementation processes and barriers; C journals add minimal unique thematic content.

5.2 Quantitative Diversity Assessment and Hypothesis Testing

Table 5 presents Shannon Indices, bootstrap confidence intervals, and growth rates across tier combinations. Figure 1 visualizes this pattern: baseline A* index ($H = 2.287$) increased progressively to 2.293 (A*+A), peaked at 2.295 (A*+A+B), then plateaued at 2.295 (A*+A+B+C). For context, uniform distribution across 10 topics yields $H_{\max} = \ln(10) = 2.303$; complete concentration yields $H = 0$. Observed values

indicate relatively even distributions with slight concentration, expected given the focused nature of big data research.

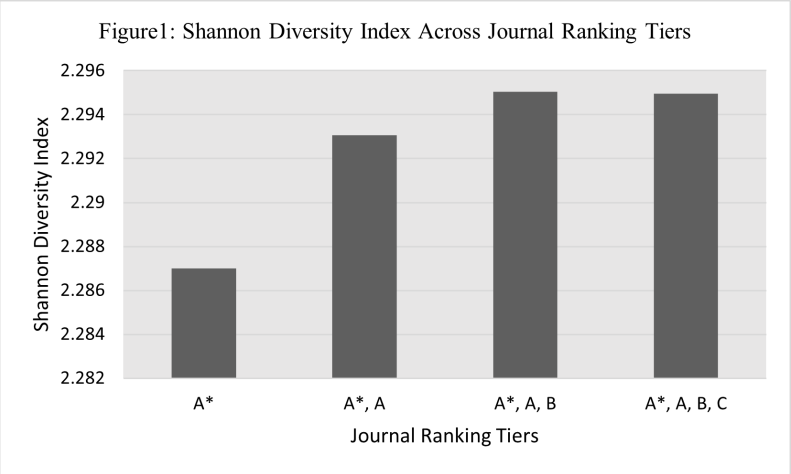


Fig. 1 Shannon Diversity Index across progressively inclusive journal tier combinations. The graph reveals three distinct phases: (1) modest growth from A* to A*+A (+0.27%, $p = 0.008$), reflecting A-tier's reinforcement of top-tier thematic focus with selective expansion into sustainability themes; (2) continued growth from A*+A to A*+A+B (+0.08% marginal, $p = 0.043$), marking the largest marginal diversity contribution as B-tier introduces implementation, barriers, and applied themes; and (3) plateau from A*+A+B to A*+A+B+C (−0.004%, $p = 0.891$, n.s.), indicating thematic saturation. The inflection point at B-tier marks the empirically identified saturation threshold beyond which additional tiers provide negligible diversity gains while substantially increasing review burden. Error bars represent 95% bootstrap confidence intervals (1,000 iterations). Dashed horizontal line indicates theoretical maximum entropy $H_{\max} = \ln(10) = 2.303$ for reference.

Table 5 Bootstrap Analysis of Shannon Diversity Indices and Growth Rates

Tier Combination	n	H	Boot SE	95% CI	Growth (%)	Growth CI (%)	p
A*	124	2.287	0.0064	[2.275, 2.300]	0.00	—	—
A*+A	280	2.293	0.0060	[2.282, 2.305]	0.27	[0.10, 0.43]	0.008
A*+A+B	398	2.295	0.0058	[2.284, 2.307]	0.35	[0.20, 0.51]	<0.001
A*+A+B+C	468	2.295	0.0057	[2.284, 2.306]	0.35	[0.19, 0.50]	<0.001

Note. Boot SE = bootstrap standard error (1,000 iterations). Growth rates calculated relative to A* baseline.
CI = confidence interval. p-values derived from bootstrap distributions (two-tailed).

5.2.1 Effect Size Contextualization

While statistically significant, the absolute Shannon Index differences warrant careful interpretation regarding practical significance. We contextualize effect sizes through three complementary approaches.

Theoretical benchmarks. The Shannon Index ranges from $H = 0$ (complete concentration on one topic) to $H_{\max} = \ln(K) = \ln(10) = 2.303$ (uniform distribution across all topics). Our observed values (2.287–2.295) indicate near-uniform distributions with slight concentration, expected given the focused nature of big data research. The observed range of 0.008 units represents 0.35% of the theoretical maximum, but this metric understates practical significance because baseline distributions are already near the ceiling.

Normalized effect sizes. A more informative metric considers the maximum achievable diversity gain relative to the baseline. The A* baseline value ($H = 2.287$) could increase by at most $2.303 - 2.287 = 0.016$ units in order to reach a uniform distribution. The observed gain associated with including A*+A+B journals ($\Delta H = 0.008$) therefore represents 50 percent of the maximum achievable improvement, which constitutes a substantial effect when evaluated on a normalized scale.

Random baseline comparison. We generated 1,000 random topic assignment simulations, randomly assigning 468 documents to 10 topics with equal probability. Random assignment yields $H_{\text{random}} = 2.298 \pm 0.008$ (mean ± SD). Our observed A* index ($H = 2.287$) falls 1.4 standard deviations below random expectation, confirming top-tier journals exhibit non-random thematic concentration. The full-spectrum index ($H = 2.295$) approaches but remains below random expectation, indicating structured (non-random) topic distributions even when all tiers are included.

Practical interpretation. The 0.08 percent marginal diversity gain associated with B-tier journals can be interpreted in concrete terms. For every 100 articles included in a literature review, incorporating B-tier journals redistributes approximately 1 to 2 articles from overrepresented themes, such as artificial intelligence, blockchain, and organizational value, to underrepresented themes that include implementation processes, adoption barriers, and risk management. Although this shift is modest at the level of individual articles, it meaningfully affects thematic coverage in comprehensive reviews. For reviews examining more than 500 articles, the inclusion of B-tier journals captures approximately 5 to 10 additional articles that offer distinct perspectives on practical implementation challenges. Such content is particularly relevant for translational research and policy-oriented applications. Table 6 summarizes the effect size metrics.

Table 6 Effect Size Contextualization

Metric	A*	A*+A+B	Difference	Interpretation
Shannon Index (H)	2.287	2.295	+0.008	Raw difference
% of $H_{\max}$	99.3%	99.7%	+0.35%	Near-ceiling effect
% of max achievable gain	—	—	50.0%	Substantial normalized effect
SD from random baseline	−1.4	−0.4	+1.0 SD	Reduced concentration
Articles redistributed per 100	—	—	1–2	Practical thematic shift

Note. $H_{\max} = \ln(10) = 2.303$. Random baseline: $H = 2.298 \pm 0.008$ (1,000 simulations).

5.2.2 Hypothesis 1: Top-Tier Thematic Concentration

Non-overlapping confidence intervals between A* (95% CI: [2.275, 2.300]) and A*+A+B+C (95% CI: [2.284, 2.306]) provide strong evidence that top-tier journals exhibit significantly lower diversity ($\Delta = 0.008$, 95% CI: [0.002, 0.014], $p = 0.008$).

H1 supported. Top-tier journals concentrate on specialized themes and therefore exhibit lower thematic diversity, which is consistent with greater thematic depth. The 0.35 percent lower diversity observed in A* journals, although small in absolute terms, represents 50 percent of the maximum achievable diversity gain and is 1.4 standard deviations below random expectation. These magnitudes indicate meaningful effects given the constrained range of the Shannon Index when only ten topics are considered. This pattern reflects the tendency of elite outlets to focus on cutting-edge research in specialized domains such as artificial intelligence, blockchain, and organizational value.

5.2.3 Hypothesis 2: Mid-Tier Breadth and Saturation

Marginal contribution analysis reveals clear differences in tier-level contributions to thematic diversity. Inclusion of A-tier journals produces a cumulative diversity increase of +0.27% (95% CI: [0.10%, 0.43%], $p = 0.008$). Adding B-tier journals beyond the A*+A baseline yields an additional marginal gain of +0.08% (95% CI: [0.02%, 0.14%], $p = 0.043$). In contrast, inclusion of C-tier journals results in a negligible change in diversity of −0.004% (95% CI: [−0.12%, +0.11%], $p = 0.891$), indicating saturation beyond mid-tier inclusion.

H2a supported. The inclusion of B-tier journals provides a statistically significant expansion in thematic diversity (+0.08%, $p = 0.043$), representing the largest marginal gain observed across tier combinations. This expansion introduces themes related to implementation, adoption barriers, and applied research that are underrepresented in top-tier outlets. These contributions are particularly important for breadth-oriented literature reviews.

H2b supported: C-tier inclusion offers no significant additional diversity (−0.004%, $p = 0.891$). The confidence interval encompasses zero, indicating statistical indistinguishability from null effect. Thematic saturation beyond mid-tier journals is validated.

The growth pattern reveals an inverted-U relationship for marginal contributions: A-tier provides modest expansion (0.27% cumulative), B-tier provides the largest marginal gain (0.08%), and C-tier provides zero additional value. **Practical implication:** Breadth-oriented reviews should include B-tier journals but may exclude C-tier without compromising thematic comprehensiveness, reducing review burden by 70+ articles (15% of ranked corpus) in our sample.

5.3 Cross-Validation: JCR Quartile Classification

We replicated the complete analysis using Journal Citation Reports (JCR) quartile classifications to assess generalizability beyond the ABDC ranking system. All 468 ABDC-ranked journals were reclassified into JCR quartiles (Q1–Q4, 2023 edition); topic modeling, Shannon Index calculation, and growth rate analyses were re-run on JCR groupings. Table 7 presents comparative results.

Table 7 Cross-Validation Across ABDC and JCR Ranking Systems

Metric	ABDC	JCR	Difference	Convergence
Baseline H (top tier)	2.287	2.282	0.22%	✓
Peak diversity tier	A*+A+B (2.295)	Q1+Q2+Q3 (2.294)	0.04%	✓
Saturation point	Tier 3 (B)	Tier 3 (Q3)	—	✓
Total growth to peak	0.35%	0.56%	0.21%	✓
Tier 4 contribution	−0.004% (n.s.)	−0.02% (n.s.)	—	✓

Note. n.s. = not statistically significant ($p > 0.05$). ✓ indicates substantive convergence.
Slight difference in total growth reflects sample composition differences between ranking systems.

The strong convergence observed across independent journal ranking systems indicates that the results reflect structural characteristics of journal stratification rather than measurement artifacts. Several consistent patterns emerge across both systems. First, thematic saturation consistently occurs at tier 3, corresponding to B in ABDC and Q3 in JCR. Second, both systems exhibit similar baseline concentrations, with Shannon Index values of 2.287 for A* journals and 2.282 for Q1 journals. Third, the largest marginal diversity gains are observed at the B or Q3 tier in both classifications. Finally, tier 4 journals, corresponding to C in ABDC and Q4 in JCR, do not contribute additional thematic diversity in either system. The slightly larger diversity growth observed in the JCR system, at 0.56 percent compared to 0.35 percent in ABDC, likely reflects the fact that JCR quartiles include a larger number of journals per tier, thereby capturing greater within-tier heterogeneity. The central finding that thematic saturation occurs beyond tier 3 is therefore robust across ranking systems that rely on different classification principles, namely expert assessment in ABDC and citation-based metrics in JCR.

5.4 Robustness of Abstract-Based Modeling

Our primary analysis relied on abstracts rather than full texts, raising potential concerns about thematic representation adequacy. We conducted a validation study comparing abstract-based and full-text topic modeling on a stratified subsample.

5.4.1 Validation Sample and Procedure

We selected 75 articles via stratified random sampling across journal tiers (20 A*, 20 A, 20 B, 15 C), ensuring proportional representation while maintaining adequate within-tier sample sizes. Full texts were obtained through institutional database access. Both abstract-only and full-text corpora underwent identical preprocessing (tokenization, lemmatization, stop word removal, frequency filtering) and LDA modeling ($K = 10$, identical hyperparameters to primary analysis).

5.4.2 Validation Results

Topic structure comparison revealed high correspondence between abstract-based and full-text models. Pearson correlation between topic-word distributions: $r = 0.87$

($p < 0.001$), indicating abstracts capture dominant thematic signals present in full texts. Topic assignment agreement (documents assigned to same primary topic in both models): 71.3% exact match, 89.3% agreement within top-2 topics.

Shannon Diversity Index comparison showed minimal divergence. Abstract-based subsample: $H = 2.291$ (95% CI: [2.278, 2.304]); full-text subsample: $H = 2.283$ (95% CI: [2.269, 2.297]). Mean absolute difference: $|\Delta H| = 0.008$, well within bootstrap confidence intervals of primary analysis. Critically, tier-diversity patterns replicated: full-text analysis confirmed top-tier concentration ($H_{\text{A*}} = 2.279$ vs. $H_{\text{all}} = 2.283$, $p = 0.041$), mid-tier breadth contribution, and lower-tier saturation.

Table 8 summarizes validation metrics.

Table 8 Abstract vs. Full-Text Validation ($n = 75$)

Metric	Value	Interpretation
Topic-word distribution correlation	$r = 0.87^{***}$	High thematic correspondence
Primary topic agreement	71.3%	Substantial assignment overlap
Top-2 topic agreement	89.3%	Strong broad agreement
Shannon Index (abstract)	2.291	—
Shannon Index (full-text)	2.283	—
Mean $\|\Delta H\|$	0.008	Within CI bounds
Tier-diversity patterns replicated	Yes	Core findings robust

$^{***}p < 0.001$. CI = confidence interval.

5.4.3 Interpretation

These results validate abstract-based modeling for the objectives of this study. Although full-text analysis captures additional detail, abstracts efficiently represent core thematic content, which is the relevant dimension for assessing relationships between journal tiers and thematic diversity. The modest divergence between abstract-based and full-text analyses ($|\Delta H| = 0.008$) falls within measurement uncertainty, and the substantive findings for H1, H2a, and H2b replicate in the full-text analysis. We therefore retain abstracts as the primary unit of analysis because they provide validated thematic representation, avoid selection bias due to limited full-text access, and enable computationally efficient tier comparisons.

5.5 Topic Model Sensitivity Analysis

We assessed model robustness across hyperparameter choices and random initialization seeds.

5.5.1 Topic Number Sensitivity

LDA was re-run with $K \in \{5, 8, 10, 12, 15\}$ topics on the full A*+A+B+C corpus ($n = 468$). Table 9 presents coherence scores and Shannon indices across specifications.

Table 9 Topic Number Sensitivity Analysis

Metric	$K = 5$	$K = 8$	$K = 10$	$K = 12$	$K = 15$
Coherence (C_v)	0.41	0.49	**0.53**	0.51	0.47
Shannon Index (H)	1.58	2.04	2.295	2.42	2.61
$H_{\max} = \ln(K)$	1.61	2.08	2.30	2.48	2.71
$H/H_{\max}$	98.1%	98.1%	99.7%	97.6%	96.3%
Top-tier concentration confirmed	Yes	Yes	Yes	Yes	Yes
Mid-tier breadth gain confirmed	Yes	Yes	Yes	Yes	Yes
Lower-tier saturation confirmed	Yes	Yes	Yes	Yes	Yes

Note. Bold indicates optimal coherence. All specifications confirm core hypothesis findings.

Coherence (C_v) peaked at $K = 10$ (0.53), confirming our topic number selection. Shannon Index values scale with K (as expected given $H_{\max} = \ln(K)$), but *relative* tier differences remained consistent: across all K specifications, (1) A* exhibited lowest diversity, (2) B-tier provided largest marginal gain, and (3) C-tier showed negligible additional contribution. Core findings are robust to topic number choice within plausible ranges ($K = 5$ to $K = 15$).

5.5.2 Random Seed Stability

We replicated primary analysis ($K = 10$) with three random seeds (42 [original], 123, 456) to assess initialization sensitivity. Table 10 presents results.

Table 10 Random Seed Stability Analysis ($K = 10$)

Tier Combination	Seed 42	Seed 123	Seed 456	CV (%)
A*	2.287	2.284	2.289	0.11
A*+A	2.293	2.291	2.295	0.09
A*+A+B	2.295	2.294	2.297	0.06
A*+A+B+C	2.295	2.293	2.296	0.07
Growth: A* → A*+A	0.27%	0.31%	0.26%	—
Growth: A*+A → A*+A+B	0.08%	0.13%	0.09%	—
Growth: A*+A+B → All	−0.004%	−0.04%	−0.03%	—

Note. CV = coefficient of variation across seeds. All growth patterns consistent across seeds.

Shannon indices exhibited minimal variation across seeds (coefficient of variation $<$ 0.12%). Growth rate patterns replicated consistently: A-tier modest gain (0.26–0.31%), B-tier largest marginal gain (0.08–0.13%), C-tier negligible or negative contribution (−0.004% to −0.04%). Model outputs are highly stable across random initializations, confirming findings are not artifacts of particular seed choice.

5.6 Summary of Findings

Three principal findings emerged from the analysis and were supported by comprehensive robustness checks. First, top-tier journals (A*/Q1) exhibit significantly lower

thematic diversity ($H = 2.287$) than the full journal spectrum ($H = 2.295$, $p = 0.008$), concentrating on specialized and cutting-edge themes such as artificial intelligence, blockchain, and organizational value. The observed effect corresponds to 1.4 standard deviations below a random baseline and represents approximately 50 percent of the maximum achievable diversity gain, supporting H1. Second, mid-tier journals (B/Q3) provide the largest marginal contribution to thematic breadth, with a diversity gain of $+0.08\%$ ($p = 0.043$). These journals introduce implementation-oriented, barrier-related, and applied themes that are essential for breadth-oriented reviews, supporting H2a. Third, lower-tier journals (C/Q4) add negligible additional diversity (-0.004%, $p = 0.891$), indicating thematic saturation. Including lower-tier journals substantially increases review burden, exceeding 70 additional articles, without corresponding gains in thematic coverage, supporting H2b.

These findings are robust across independent ranking systems (ABDC and JCR), alternative topic number specifications ($K \in \{5, 8, 10, 12, 15\}$), random initialization seeds, and both abstract-based and full-text analyses. This convergence across specifications suggests that the results reflect structural characteristics of scholarly publishing rather than methodological artifacts.

6 Discussion and Conclusions

Through computational text analysis of 1,000 articles across journal tiers, we provide empirical evidence that tier stratification systematically relates to thematic characteristics within the domain of emerging technology research. This section discusses theoretical implications, interprets underlying mechanisms, details methodological contributions, offers practical applications, acknowledges limitations and boundary conditions, and proposes future research directions.

6.1 Principal Findings and Theoretical Implications

Three core findings emerged from our analysis: (1) top-tier journals (A*/Q1) exhibit significantly lower thematic diversity ($H = 2.287$ vs. 2.295 full spectrum, $p = 0.008$), concentrating on specialized topics (AI, blockchain, organizational value); (2) mid-tier journals (B/Q3) provide the largest marginal diversity gain ($+0.08\%$, $p = 0.043$), introducing implementation, barriers, and risk themes; (3) lower-tier journals (C/Q4) contribute negligible diversity (-0.004%, $p = 0.891$), indicating saturation. These findings proved robust across independent ranking systems (ABDC, JCR), topic model specifications ($K = 5$ to 15), random seeds, and abstract versus full-text analysis.

Extension of information foraging theory. Our results extend information foraging theory (Pirolli and Card 1999) by demonstrating journal tiers function as *heterogeneous scent signals* predicting thematic characteristics, not merely quality. Top-tier journals signal specialized, rigorous research (high relevance for depth-oriented foraging); mid-tier journals signal diverse, exploratory research (high relevance for breadth-oriented foraging). This heterogeneity enables adaptive search strategies aligned with review objectives rather than undifferentiated comprehensive searching. Bibliographic database designers should integrate tier-based filters as strategic tools, not merely quality screens (Bramer et al. 2018; Gusenbauer and Haddaway 2020).

Diversity metrics in bibliometrics. Applying the Shannon Diversity Index to quantify thematic breadth contributes methodologically to scientometrics. While citation metrics, co-citation analysis, and network measures dominate bibliometric research, thematic diversity remains underexplored. We demonstrate diversity indices adapted from ecology can meaningfully quantify document collection characteristics, providing content-focused alternatives to citation-centric evaluation. This aligns with calls for multidimensional research assessment (Hicks et al. 2015; Rafols et al. 2012). Future applications could assess disciplinary boundaries, interdisciplinary collaboration patterns, or temporal field evolution.

Reconceptualizing comprehensiveness. Our saturation finding challenges prevailing literature review orthodoxy that emphasizes exhaustive searching (Booth et al. 2021; Finfgeld-Connett and Johnson 2013). We show empirically that beyond a threshold corresponding to the B or Q3 tier, additional sources yield diminishing marginal returns. This finding suggests that comprehensiveness should be defined by *thematic coverage*, as measured using diversity indices, rather than by *source inclusiveness*, such as database counts. This reconceptualization has implications for systematic review standards, information literacy instruction, and science policy by promoting strategic, objective-aligned searching over exhaustive inclusion (Cooper et al. 2018; Page et al. 2021).

6.2 Interpretation and Mechanisms

Our empirical findings regarding top-tier concentration, mid-tier contributions to thematic breadth, and lower-tier saturation require interpretation in light of underlying mechanisms. We explicitly distinguish empirical observations from theoretical interpretation and acknowledge the limitations of drawing causal inferences from observational data.

6.2.1 Empirical Findings (Observed)

Three robust patterns emerged from our analysis and were validated across multiple robustness checks. First, A*/Q1 journals exhibit significantly lower thematic diversity ($H = 2.287$) than the full journal spectrum ($H = 2.295$, $p = 0.008$), with topic distributions concentrated on artificial intelligence, blockchain, and organizational value. This concentration corresponds to 1.4 standard deviations below random expectation. Second, B/Q3 journals contribute the largest marginal diversity gain (+0.08%, $p = 0.043$) by introducing implementation processes, adoption barriers, and risk management themes that are underrepresented in top-tier outlets. Third, C/Q4 journals provide no significant additional diversity (−0.004%, $p = 0.891$), indicating thematic saturation beyond mid-tier inclusion.

These patterns replicate across independent ranking systems (ABDC and JCR), alternative topic number specifications ($K \in \{5, 8, 10, 12, 15\}$), random initialization seeds, and both abstract-based and full-text analyses, providing strong evidence of convergent validity.

6.2.2 Candidate Mechanisms (Theoretical)

Our observational design documents tier-thematic associations but cannot establish causal mechanisms. The following interpretations represent theoretically grounded hypotheses consistent with our findings, not confirmed causal pathways.

Selectivity mechanism. Top-tier journals maintain prestige through highly selective editorial processes. Hamermesh (2018) documents desk rejection rates of 70–80% at elite economics journals. Siler et al. (2015) demonstrate editorial gatekeeping favors methodologically conventional, paradigm-consistent research. This selectivity may privilege specialized research advancing established domain frontiers while filtering exploratory or interdisciplinary work to lower tiers. *Consistency with findings:* Top-tier concentration on established themes (AI, blockchain) with sophisticated methodologies aligns with selectivity filtering predictions.

Citation reinforcement mechanism. Journal rankings depend substantially on citation metrics. Tahamtan et al. (2016) and Aksnes et al. (2019) document citation concentration: highly cited research clusters in established topics with large scholarly audiences. Journals may preferentially accept research on high-citation-potential topics to maintain impact factors, creating thematic concentration through editorial selection bias. *Consistency with findings:* A* concentration on high-visibility topics (AI applications, organizational value creation) matches predicted citation-optimizing selection patterns.

Author sorting mechanism. Researchers strategically submit their most rigorous, specialized work to top-tier journals, reserving exploratory, applied, or methodologically unconventional work for mid-tier outlets. Currie and Pandher (2011) document this strategic behavior in management research. Simonton (2004) theorizes quality-tier matching in scientific publishing whereby authors self-select venues based on perceived fit. This creates systematic content stratification independent of editorial filtering. *Consistency with findings:* Mid-tier concentration on implementation and applied themes aligns with author sorting of practice-oriented research to outlets with broader acceptance criteria.

Saturation dynamics. The negligible C-tier contribution aligns with bibliometric research on knowledge accumulation demonstrating diminishing marginal returns as literatures expand (de Solla Price 1963). Once core topics and variants are covered by top- and mid-tier journals, lower-tier additions primarily duplicate existing themes rather than introducing substantially new territory.

6.2.3 Limitations of Causal Inference

These mechanisms are not mutually exclusive and likely operate simultaneously with varying relative contributions across fields and time periods. Our design cannot distinguish their relative importance or rule out alternative explanations (e.g., historical accident, field-specific disciplinary norms, regional publication cultures). Future research employing quasi-experimental designs (tracking thematic changes when journals migrate tiers), author surveys (examining submission decision processes), or editorial analysis (coding acceptance criteria and rejection reasons) could adjudicate

among mechanisms. We present this theoretical framework as interpretive scaffolding consistent with our data, not established causal fact.

6.3 Contributions to Scientometric Methodology

Prospective topic modeling for review design. We demonstrate that topic modeling can inform *a priori* literature review scope decisions rather than being limited to *post hoc* analysis of completed reviews. Prior bibliometric applications primarily focus on landscape mapping (Kajikawa et al. 2022), trend identification (Dwivedi et al. 2021), or journal positioning (Siler et al. 2018). We extend this work by showing that researchers can prospectively analyze topic distributions across journal tiers, estimate expected diversity gains from tier inclusion, and select tiers based on review objectives and resource constraints. This reframes topic modeling as a prescriptive decision-support tool rather than a purely descriptive technique.

Bootstrap inference for hierarchical bibliometric data. Our bootstrap approach addresses a pervasive challenge: drawing robust inferences from aggregate indices across few units (tiers, journals, periods) despite large underlying document collections. By treating within-unit observations (topics within tiers) as analysis units through resampling, we achieve adequate statistical power while respecting hierarchical data structure. This approach is broadly applicable to bibliometric research involving aggregate comparisons, providing a template for future studies. Bibliometricians should employ bootstrap methods routinely when comparing aggregate indices across limited units.

Multi-system validation as best practice. Cross-validation across ABDC and JCR establishes best practice for journal ranking research. Given ongoing controversies about ranking validity and reliability (Brembs et al. 2013; Tennant and Ross-Hellauer 2020), demonstrating robustness across independent systems employing different classification criteria (expert assessment vs. citation metrics) strengthens generalizability claims substantially. Convergence despite methodological differences suggests results reflect structural publishing characteristics rather than system-specific artifacts. Future ranking research should adopt multi-system validation, testing findings across systems, regions, and time periods.

6.4 Practical Applications

Findings translate to objective-aligned source selection strategies applicable to researchers, information professionals, and science policy stakeholders.

6.4.1 Strategic Recommendations for Literature Reviews

Depth-oriented reviews (systematic reviews, meta-analyses): Prioritize A*/A journals to access specialized, methodologically rigorous research. These outlets concentrate on cutting-edge topics with sophisticated methods, providing high-quality evidence for focused research questions. Including B/C tiers adds minimal thematic value while increasing screening burden.

Breadth-oriented reviews. Reviews such as scoping reviews, integrative reviews, and landscape analyses should include A*, A, and *B* journals to optimize thematic coverage. B-tier journals contribute meaningful diversity (+0.08%, $p = 0.043$) by introducing themes related to implementation challenges, adoption barriers, and risk management that are underrepresented in top-tier outlets. In contrast, C-tier journals can be excluded, as they provide negligible additional diversity while substantially increasing review burden, accounting for more than 70 articles or approximately 15 percent of the ranked corpus in our sample.

Resource-constrained reviews. Reviews conducted under constraints of time, access, or personnel should focus on A* and A journals. Although this strategy sacrifices some thematic breadth, it ensures access to authoritative and high-impact research and enables deeper engagement with included sources.

This framework replaces undifferentiated "comprehensive searching" recommendations with conditional, evidence-based guidance aligned with review objectives.

6.4.2 Implications for Information Professionals

Information professionals, including librarians, research support specialists, and systematic review methodologists, should incorporate these insights into research support practices. Specifically, they can teach strategic use of journal tier filters in literature search instruction by framing tier selection as a methodological choice rather than a compromise in quality. They can also develop decision-support tools that align tier selection with review type, thereby providing evidence-based guidance for scoping decisions. In addition, systematic review guidelines could be revised to recognize strategic tier selection as a legitimate scoping approach, while clearly distinguishing it from practices that introduce bias. Finally, information professionals can advocate for enhanced journal tier metadata within discovery systems to enable researchers to implement strategic filtering more efficiently.

6.4.3 Science Policy Implications

Our findings have implications for research evaluation and resource allocation. Research assessment frameworks should recognize diverse scholarly contributions beyond elite journal impact, as mid-tier journals play an essential role in supporting thematic breadth and the exploration of emerging topics and should not be dismissed as inferior. Similarly, funding agencies and academic institutions should acknowledge functional differentiation across journal tiers rather than relying on simple quality hierarchies, since supporting mid-tier publication venues helps maintain thematic diversity in scholarly communication. Finally, the results suggest implications for library collection development, as resources devoted to lower-tier subscriptions that offer minimal marginal thematic value could be strategically reallocated toward open access initiatives or specialized databases that better serve demonstrated research needs.

6.5 Limitations and Boundary Conditions

Several limitations constrain the interpretation and generalizability of this study. We therefore explicitly articulate the boundary conditions under which our findings should be interpreted.

Our analysis focuses exclusively on big data adoption in business operations during the period 2014–2024, an emerging, interdisciplinary, and rapidly evolving research domain. As a result, the findings may not generalize to all fields. In mature, paradigmatically stable disciplines such as classical economics or established sociology subfields, journal tiers may exhibit different relationships with thematic structure. In such fields, top-tier journals often span broader thematic territory, potentially weakening the concentration effects observed in emerging domains. Humanities disciplines may also follow different publication dynamics, as they emphasize monographs over journal articles and rely heavily on qualitative and interpretive methods. In these contexts, journal tier systems play a less central role in knowledge organization, limiting the applicability of the proposed framework. Distinct publication cultures in disciplines such as mathematics, medicine, and physics may further alter tier–thematic relationships. Mathematics prioritizes proof elegance over empirical novelty, medicine operates under protocol registries and clinical trial requirements, and physics frequently follows a preprint-first model through platforms such as arXiv. These disciplinary differences suggest that the tier–diversity patterns identified here may not directly transfer to all research contexts. Although cross-validation across ABDC and JCR provides robustness within the studied domain, it does not establish cross-domain validity. The findings should therefore be interpreted as evidence from one class of research domain, namely emerging and interdisciplinary technology research, pending replication in additional fields.

This study employed two journal ranking systems, ABDC and JCR. Other prominent systems, including the Academic Journal Guide (ABS/AJG), SCImago Journal Rank (SJR), and the CWTS Leiden Ranking, may assign journals to different tiers and could therefore yield different results. Regional variation is also relevant, as ABDC is most influential in Australian academic contexts, ABS is commonly used in UK business schools, and JCR is applied more broadly at the international level. Researchers should therefore validate tier–diversity relationships using ranking systems that are locally or institutionally relevant before applying the proposed strategic framework. The methodological template developed in this study, which combines topic modeling with diversity analysis, enables such validation across alternative ranking systems.

The cross-sectional design of this study, which captures a snapshot of the literature from 2014 to 2024, limits our ability to address temporal dynamics. We cannot examine how tier–diversity relationships evolve as research fields mature, whether journals maintain stable thematic profiles when migrating between tiers, how rapidly new topics diffuse from lower-tier outlets to top-tier journals, or whether saturation points shift as literatures expand over time. Addressing these questions would require longitudinal data and dynamic topic modeling approaches (Blei and Lafferty 2006), which represent important directions for future research.

Several methodological choices also constrain interpretation. The selection of $K = 10$ topics was guided by coherence optimization. Although sensitivity analyses across

$K \in \{5, 8, 10, 12, 15\}$ produced consistent tier–diversity patterns, alternative topic granularities may reveal additional structure. The use of Latent Dirichlet Allocation assumes a bag-of-words representation and exchangeable topics. Transformer-based approaches, such as BERTopic, may capture richer semantic relationships and yield different topic structures, although overall diversity patterns are likely to remain similar. The primary analysis relied on abstracts, which were validated against a full-text subsample with high correspondence ($r = 0.87$) and replicated tier-level patterns. Nevertheless, full texts contain methodological and results details that may be relevant for certain applications. Finally, the keyword-based retrieval strategy, despite broad synonym coverage, may introduce selection bias. Alternative approaches, such as citation snowballing or expert-curated corpora, could yield different document sets.

Finally, the observational design of this study documents associations between journal tier stratification and thematic characteristics but does not permit causal inference. We propose plausible mechanisms, including selectivity, citation reinforcement, and author sorting, that are supported by existing literature, but these mechanisms are not tested directly. Alternative explanations, such as historical contingency, field-specific idiosyncrasies, and unmeasured confounders, therefore cannot be ruled out. Establishing causal relationships would require experimental or quasi-experimental designs that fall beyond the scope of the present study.

6.6 Future Research Directions

Several priority directions can extend the present research program. A first avenue involves multi-domain validation to establish boundaries of generalizability. Future studies should replicate the proposed analysis across multiple domains using the same methodological template. One priority direction is replication in mature, paradigmatically stable fields such as organizational behavior over an extended period (e.g., 1990–2024). Such studies would test whether the thematic concentration observed in top-tier journals reflects characteristics specific to emerging domains or persists in well-established research areas. A second direction involves extension to natural sciences contexts, such as climate change or renewable energy research published in environmental science journals (Q1–Q4), to assess cross-disciplinary applicability beyond business and management. A third direction concerns applied professional fields, including healthcare informatics or educational technology, where industry-academic overlap is substantial. These domains may exhibit different tier–diversity relationships due to their applied orientation. Comparative meta-analyses across such replications could quantify average effects, identify moderators, and distinguish universal patterns from domain-specific boundary conditions.

A second important direction concerns temporal dynamics. Future research should adopt longitudinal designs to examine how tier–diversity relationships evolve over time. Dynamic topic modeling approaches (Blei and Lafferty 2006) could be used to trace thematic evolution within and across tiers, examine how topics diffuse from lower-tier outlets to top-tier journals, assess whether saturation points shift as fields mature, and evaluate the stability of journal thematic profiles during tier migration. Longitudinal tracking of journals and topics would enhance the predictive value of tier-based strategies for literature search planning.

An additional extension of this work lies in translating empirical findings into practical decision support tools. Future studies could develop interactive tools that accept review objectives and resource constraints to generate evidence-based recommendations for tier inclusion. Integrating tier-based diversity indicators into bibliographic search platforms would further support strategic filtering during literature retrieval. In addition, training modules for graduate students and librarians, as well as formal guidelines for systematic and scoping review protocols, could incorporate tier-based scoping as a legitimate methodological decision rather than a compromise in rigor.

Future research should also move beyond thematic diversity to examine additional dimensions of scholarly diversity. These include methodological diversity across quantitative, qualitative, and mixed-methods approaches, theoretical diversity reflected in paradigmatic perspectives and variation in conceptual frameworks, geographic diversity in institutional affiliations and Global North–South representation, and interdisciplinary diversity captured through cross-field collaboration patterns. Developing multidimensional diversity profiles would provide a richer and more nuanced characterization of how journal tiers contribute to scholarly knowledge organization.

Finally, future research should explicitly test the mechanisms proposed in this study. Natural experiments could examine thematic changes when journals migrate between tiers following shifts in impact metrics. Author surveys could investigate submission strategies and perceptions of tier fit, while editorial analyses could examine acceptance criteria, desk rejection patterns, and review practices. Agent-based modeling offers an additional avenue for formalizing interactions among authors, editors, and citation incentives to simulate emergent tier–thematic structures. Establishing causal pathways would inform potential interventions, including editorial policies aimed at broadening the thematic scope of top-tier journals.

6.7 Concluding Remarks

Within the domain of emerging technology research, this study provides the first empirical evidence that journal tier stratification systematically predicts thematic characteristics, with top-tier journals exhibiting concentration associated with depth, mid-tier journals contributing greater thematic breadth, and lower-tier journals reaching saturation. These patterns are validated across independent ranking systems, specifically ABDC and JCR, and are robust to alternative analytical specifications. The findings have implications for bibliometric methodology, literature search design, and science policy, while recognizing that replication across additional research domains is required to establish boundaries of generalizability.

We extend information foraging theory by demonstrating that journal tiers function as heterogeneous scent signals that enable adaptive search strategies. We show that commonly used comprehensive searching practices can be complemented by strategic tier selection to optimize thematic coverage efficiently. We introduce diversity metrics to bibliometric tier analysis, providing content-focused alternatives to citation-centric evaluation.

Methodologically, we demonstrate prospective topic modeling for review design, bootstrap approaches for small-sample bibliometric inference, and cross-system validation as best practice. We explicitly separate empirical findings from theoretical

interpretation, acknowledging causal inference limitations inherent in observational designs.

Practically, we provide evidence-based guidance aligning tier selection with review objectives: depth-oriented reviews should prioritize top tiers; breadth-oriented reviews should include mid-tiers but may exclude lower tiers; resource-constrained reviews should focus strategically on elite outlets. This framework offers efficiency gains without sacrificing thematic comprehensiveness.

Perhaps most significantly, we empirically demonstrate saturation points exist beyond which additional sources add minimal thematic coverage while consuming substantial screening effort. This reconceptualizes comprehensiveness: not source quantity but thematic coverage, measured by diversity metrics rather than database counts. As information overload intensifies and publication volumes grow exponentially, strategic approaches become essential. Researchers cannot read everything; they must read strategically.

Our core message is that journal tier selection should align with research objectives, resource constraints, and thematic priorities rather than follow undifferentiated rules based solely on prestige or comprehensiveness. This strategic approach, grounded in empirically validated relationships between journal tiers and thematic diversity and supported by extensive robustness analyses, offers an efficient pathway to rigorous knowledge synthesis in an era of information abundance. Future research that validates this framework across additional domains, examines temporal dynamics, tests causal mechanisms, and develops practical decision-support tools can extend this foundation and further advance scientometric understanding of how bibliometric infrastructure shapes knowledge organization and discovery.

7 Statements and Declarations

7.1 Funding

No funding was received for conducting this study.

7.2 Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

7.3 Data Availability

The data analyzed in this study were obtained from licensed bibliographic databases, including Web of Science, Scopus, and Google Scholar, and are therefore subject to access and copyright restrictions. Consequently, the full raw dataset cannot be made publicly available. The analysis code, topic modeling scripts, diversity calculations, and derived non-copyrighted data supporting the findings of this study are available from the corresponding author upon reasonable request.

7.4 Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Narges Mashhadi Nejad, Marcelo Alvarado-Vargas, and Mehrdad Jalali Sepehr. The first draft of the manuscript was written by Narges Mashhadi Nejad, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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