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Mapping the Intellectual Architecture of Digital Technologies and Business Model Innovation: A Bibliometric Analysis of Scopus-Indexed Publications, 2004–2026

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Abstract

Research at the intersection of digital technologies and business model innovation (BMI) has expanded rapidly since the mid-2010s, yet its intellectual architecture—the conceptual foundations, influential scholars, citation anchors, and thematic clusters that give it coherence—remains poorly charted. Narrative and systematic reviews have proven insufficient to map a field now generating more than 260 peer-reviewed publications per year across at least twenty-seven disciplinary categories. This paper addresses that gap by conducting a comprehensive bibliometric analysis of 1,707 Scopus-indexed journal articles published between 2004 and early 2026. Drawing on publication trend analysis, author and institutional productivity mapping, citation and co-citation analysis, and keyword co-occurrence examination—all executed through the Biblioshiny interface of R Studio—we delineate four distinct developmental epochs that trace the field's evolution from pre-paradigmatic exploration to consolidation. Citation analysis identifies a compact set of foundational texts, anchored by Verhoef et al. (2021), Chesbrough (2010), and Ghobakhloo (2020), that continue to organise scholarly discourse across sub-fields. Keyword analysis reveals business model innovation, digital transformation, artificial intelligence, and sustainability as the field's dominant conceptual pillars, while also exposing theoretical fault lines at the boundaries of these clusters. The findings offer an empirically grounded road map for future research and establish a replicable methodological benchmark for ongoing monitoring of this rapidly evolving domain.

Keywords: business model innovation; digital technologies; bibliometric analysis; citation analysis; keyword co-occurrence; digital transformation; Scopus

1. INTRODUCTION

The relationship between digital technologies and business model innovation occupies an increasingly central position in management, information systems, and innovation research. Since the mid-2000s, scholars across multiple disciplines have documented how technologies characterised by generativity, scalability, and recombinability—from cloud computing and the Internet of Things to machine learning and blockchain—reshape the fundamental logics through which organisations create and capture value (Yoo et al., 2010; Nambisan et al., 2019). Business model innovation (BMI), understood as the deliberate redesign of how a firm articulates its value proposition, configures its activities, and appropriates returns (Foss & Saebi, 2017; Teece, 2018), has emerged as the principal conceptual instrument through which scholars and practitioners interpret these transformations. The proposition that digital technologies do not generate competitive advantage automatically, but only when embedded within reconfigured business model architectures, has become something approaching a theoretical consensus (Zott & Amit, 2008; Baden-Fuller & Haefliger, 2013; Verhoef et al., 2021).

Yet for all its contemporary salience, this research field presents a paradox. Output is accelerating—from fewer than seven publications per year before 2010 to an estimated 316 in 2025 alone—but the intellectual landscape is poorly integrated. Studies proliferate across strategy, entrepreneurship, information systems, engineering, and sustainability research, each sub-community deploying partially overlapping vocabularies, divergent theoretical assumptions, and incompatible empirical approaches (Rachinger et al., 2019; Vial, 2019; Ancillai et al., 2023). Thematic islands—digital servitization, AI-driven business models, platform ecosystems, sustainable BMI—exist in relative isolation from one another, nourished by distinct citation ecologies and mediated by different disciplinary gatekeepers (Parida et al., 2019; Zare & Persaud, 2025). The practical consequence is that researchers entering this space struggle to locate its conceptual centre of gravity, distinguish established findings from speculative claims, and identify where the most urgent theoretical gaps reside.

Bibliometric analysis offers a methodologically appropriate response to this challenge. Unlike narrative or systematic literature reviews, which are necessarily selective and subject to cognitive bias, bibliometric methods apply quantitative techniques to large bibliographic datasets, enabling researchers to map citation flows, co-authorship networks, and keyword co-occurrence structures across the entire population of relevant publications (Zupic & Čater, 2015; Donthu et al., 2021). The resulting portraits of a field's intellectual architecture are reproducible, scalable, and relatively free from the interpretive presuppositions that constrain smaller-scale qualitative syntheses. Prior bibliometric studies in this area—notably Vaska et al. (2021), Zare and Persaud (2025), and Chawla and Goyal (2022)—have made important contributions but were constrained by smaller datasets, shorter time horizons, or narrower analytical foci that prevented them from capturing the field's recent explosive growth and thematic diversification.

The present study addresses these limitations by analysing the largest and most temporally current dataset yet assembled for this domain: 1,707 peer-reviewed journal articles indexed in Scopus between 2004 and early 2026. The study pursues four interconnected objectives. First, it maps the field's publication trajectory across four developmental epochs, providing a temporally differentiated account of how scholarly engagement with digital technologies and BMI has grown and changed. Second, it identifies the most influential authors, institutions, and journals, characterising the field's intellectual leadership and the publishing venues where its core conversations are concentrated. Third, it delineates the citation landscape, pinpointing the foundational texts that anchor the field's theoretical vocabulary and tracing the intellectual debts that structure current research. Fourth, it examines keyword co-occurrence patterns to reveal the conceptual architecture of the field—the dominant themes, their internal coherence, and the fault lines that separate them. Together, these four analytical dimensions yield a comprehensive and empirically grounded map of a field at a critical juncture in its development.

The paper proceeds as follows. Section 2 reviews the theoretical background and prior literature on BMI and digital transformation. Section 3 describes the data and methodology. Sections 4 through 8 present and discuss the results of each analytical dimension. Section 9 identifies theoretical and empirical gaps, and Section 10 concludes.

2. THEORETICAL BACKGROUND

2.1 Business Model Innovation as a Conceptual Framework

Business models were first theorised as representations of a firm's commercial architecture—the configuration of resources, activities, and relationships through which it generates revenue (Zott & Amit, 2008). This early conception was largely descriptive, treating the business model as a snapshot of a firm's logic at a given moment rather than as an object of deliberate strategic transformation. The pivot towards business model innovation as an active strategic instrument gained momentum in the late 2000s, driven by the observation that firms in digital markets frequently generated competitive advantage not by developing superior products or processes, but by conceiving fundamentally different approaches to value creation and capture that rendered incumbent configurations obsolete (Chesbrough, 2010). This insight was sharpened by Foss and Saebi (2017), whose systematic review distinguished BMI from product and process innovation by its emphasis on reconfiguring the interdependent elements of a business system—value proposition, value creation activities, and value appropriation mechanisms—as an integrated whole. The integration of BMI into the dynamic capabilities framework by Teece (2018) represented a further theoretical milestone. By arguing that the capacity to innovate business models constitutes a microfoundation of dynamic capabilities, Teece reframed BMI as a higher-order organisational competence, rather than an episodic strategic response to technological disruption. This reframing has had significant downstream consequences for empirical research, directing scholarly attention towards the organisational routines, leadership orientations, and sensing-seizing-reconfiguring processes through which firms sustain iterative BMI over time (Warner & Wäger, 2019). Concurrently, Jacobides et al. (2018) extended the theoretical agenda by contextualising BMI within digital platform ecosystems, arguing that the locus of value creation and capture has shifted from the firm to the ecosystem, complicating traditional assumptions about asset ownership and competitive positioning that underpin most BMI theory.

2.2 Digital Technologies as a Driver and Disruptor of Business Model Innovation

The theoretical literature on digital technologies converges on several distinctive attributes that differentiate them from prior generations of information technology. Yoo et al. (2010) conceptualised digital artefacts as inherently generative—capable of producing unanticipated uses, combinations, and innovations beyond those envisioned by their designers—and characterised the resulting digital innovation process as one of layered modularity in which products, platforms, and services can be recombined across industry boundaries in ways that undermine traditional definitions of competitive space. Nambisan et al. (2019) extended this analysis to the context of digital entrepreneurship, arguing that the boundary conditions of digital innovation—its distributed agency, its ambiguity of outcomes, and its scalability—require substantially different organisational and strategic logics than those developed in analogue contexts.

These theoretical perspectives align with empirical findings on the mechanisms through which digital technologies reshape value chains and business models. Vial (2019) synthesised a broad body of evidence to argue that digital transformation—understood as strategic, organisation-spanning technological integration, rather than incremental operational digitisation—triggers changes in value creation, delivery, and capture that frequently require concurrent BMI. Verhoef et al. (2021) elaborated this argument by developing a multi-dimensional conceptualisation of digital transformation that distinguishes its technological, strategic, organisational, and value dimensions, providing a more granular theoretical framework for examining how digital transformation and BMI interact and co-evolve.

2.3 The Need for Bibliometric Mapping

The theoretical landscape described above, while rich, is also divided. The BMI-as-dynamic-capability stream (Teece, 2018; Warner & Wäger, 2019) tends to privilege organisational and managerial agency, while the digital innovation stream (Yoo et al., 2010; Nambisan et al., 2019) foregrounds the constitutive role of technology. The platform ecosystem perspective (Jacobides et al., 2018; Parker et al., 2016) introduces a further theoretical lens centred on inter-firm governance and network effects. Industry 4.0 research (Frank et al., 2019; Kohtamäki et al., 2019) draws on engineering and operations management traditions that are only partially commensurable with the strategic management frameworks that dominate other sub-fields. AI-driven BMI (Cockburn et al., 2019; Raisch & Krakowski, 2021) and sustainability-oriented BMI (Ghobakhloo, 2020; Bocken et al., 2022) represent the newest entrants, each importing theoretical assumptions from adjacent fields that have not yet been fully reconciled with established BMI theory.

This theoretical heterogeneity is, in part, a natural feature of a young and growing field. But it also creates genuine risks: duplicative research that asks the same questions in different disciplinary vocabularies, theoretical fragmentation that makes cumulative knowledge building difficult, and a mismatch between the field's empirical ambitions and its conceptual foundations. Identifying and characterising these dynamics—determining which theoretical strands are converging, which are developing in parallel, and which are truly isolated—requires an analytical method capable of processing the entire published literature, not merely the fraction accessible to any individual researcher. Bibliometric analysis, and specifically the combination of citation analysis and keyword co-occurrence mapping employed in this study, is precisely suited to this purpose (Ramos-Rodríguez & Ruíz-Navarro, 2004; Hota et al., 2020).

3. DATA AND METHODOLOGY

3.1 Database Selection and Search Protocol

The Scopus database was selected as the primary data source for this study on the grounds of its superior coverage of international peer-reviewed literature relative to alternative databases, its established use in bibliometric research on management and technology topics (Donthu et al., 2021), and the breadth of bibliographic metadata—including author affiliations, subject classifications, citation counts, and keyword assignments—that it makes available for systematic analysis. The search string was constructed to capture the full spectrum of research connecting digital technologies to business model innovation, combining terms from both conceptual domains using Boolean operators. The digital technologies arm of the search encompassed the following terms: digital; digitization; digitalization; ICT; blockchain; industry 4.0; internet; artificial intelligence; technological development; big data; technological change; fintech; information and communication technologies; technology adoption; cloud computing; social media; internet of things; IoT; machine learning; deep learning; and 3D printing. These terms were combined via OR operators and applied to titles, abstracts, and keywords. The BMI arm employed the search terms: business model innovation and business models innovation, combined via OR and linked to the digital arm via AND.

Inclusion criteria required publications to be: peer-reviewed journal articles; written in English; focussed on the intersection of digital technologies and business model innovation as their primary research concern; and indexed in Scopus with complete bibliographic records. Exclusion criteria eliminated books, book chapters, conference papers, editorials, and review articles, following established conventions in bibliometric research (Tranfield et al., 2003; Zupic & Čater, 2015). The temporal scope of the search was set from 2004—the earliest year for which the search string retrieved a relevant publication—to March 2026, the date at which data collection was concluded. The initial search returned 2,341 records. Following systematic screening of titles and abstracts to remove off-topic results, and a second-stage full-text assessment of borderline cases, the final dataset comprised 1,707 articles. This represents the most extensive dataset yet assembled for bibliometric analysis in this domain.

3.2 Analytical Approach

All bibliometric analyses were conducted using the Biblioshiny web interface within R Studio (version 4.3.1), which provides a comprehensive suite of bibliometric functions based on the Bibliometrix package (Aria & Cuccurullo, 2017). Four analytical techniques were applied. Publication trend analysis examined the annual distribution of articles across the study period, enabling temporal mapping of the field's growth trajectory. Author and institutional productivity analysis employed both raw article counts and fractionalised scoring—a method that apportions credit to authors in proportion to their contribution relative to the total number of co-authors, thereby providing a more accurate measure of individual scholarly output in highly collaborative research environments (Hota et al., 2020). Citation analysis ranked articles by total citations received and normalised citation scores (citations per year relative to the average citation rate for the publication year), identifying the foundational intellectual anchors of the field. Keyword co-occurrence analysis employed the Biblioshiny keyword co-occurrence network function, which maps the frequency and co-occurrence of author keywords and indexed terms, enabling identification of the conceptual clusters and thematic boundaries that structure the field's intellectual architecture (Van Eck & Waltman, 2010).

The methodological triangulation of these four approaches is deliberate. Citation analysis and keyword co-occurrence analysis address complementary facets of a field's intellectual structure: citation flows trace the genealogy of ideas—who builds on whom—while keyword co-occurrence maps the conceptual landscape—which ideas are deployed together. Together, they provide a more complete portrait of the field's intellectual architecture than either technique could achieve alone. Publication trend and productivity analyses contextualise these structural snapshots within a temporal and sociological frame, revealing who produces knowledge and at what rate of acceleration. This combination of analytical techniques follows best-practice guidelines for bibliometric research in management and organisation science (Donthu et al., 2021; Ramos-Rodríguez & Ruíz-Navarro, 2004).

4. ANNUAL SCIENTIFIC PRODUCTION AND DEVELOPMENTAL EPOCHS

4.1 The Aggregate Trajectory

The annual distribution of 1,707 articles across the 2004–2026 study period presents a pattern that is both empirically striking and theoretically informative. Growth is not smooth but proceeds through successive phases, each characterised by a distinct rate of acceleration and associated with identifiable external drivers. Table 1 summarises the annual and cumulative publication counts.

Year	Articles	Cumulative Total	Year	Articles	Cumulative Total
2004	1	1	2015	26	106
2005	0	1	2016	34	140

Year	Articles	Cumulative Total	Year	Articles	Cumulative Total
2006	4	5	2017	66	206
2007	0	5	2018	86	292
2008	1	6	2019	98	390
2009	3	9	2020	139	529
2010	10	19	2021	169	698
2011	12	31	2022	188	886
2012	9	40	2023	211	1,097
2013	19	59	2024	262	1,359
2014	21	80	2025	316	1,675

Table 1. Annual and Cumulative Publication Counts, 2004–2026 (2026 partial year). Source: Scopus; R Studio Biblioshiny.

Several features of this distribution warrant emphasis. First, the exponential character of the growth curve is pronounced: comparing the pre-2017 cumulative total (206 articles) with the post-2017 total (approximately 1,501 articles) reveals that roughly 88% of all publications in the dataset appeared in the final nine years of the study period. Second, the period 2022–2025 alone contributed approximately 977 articles, or 57% of the corpus, indicating that the field's output is accelerating rather than plateauing. Third, the partial-year 2026 figure (33 articles by March) projects an annual total exceeding 130—likely an undercount given typical publication lags—suggesting continued momentum.

4.2 Four Developmental Epochs

Phase I: Pre-Paradigmatic Exploration (2004–2012). Annual output during this phase remained below 13 articles, and the cumulative total reached only 40 publications over eight years. The intellectual character of this period is best described as pre-paradigmatic in the Kuhnian sense (Kuhn, 1962): individual scholars probed the relationship between emerging digital technologies and business model design without yet constituting a coherent research community with shared theoretical assumptions, canonical texts, or established empirical protocols. The field's precursors during this phase were primarily drawn from information systems research—particularly work on e-business models and internet economics—and early platform theory, represented by Eisenmann et al.'s (2006) work on multi-sided platforms and Chesbrough's (2007) early thinking on the role of technology in business model design.

Phase II: Formative Growth (2013–2016). Annual output nearly doubled from 19 to 34 articles during this phase, with the cumulative total rising from 59 to 140. The conceptual drivers of this acceleration are readily identifiable. The popularisation of Industry 4.0 as a policy discourse and research agenda—following the World Economic Forum's designation of the fourth industrial revolution as a defining challenge of the mid-2010s—provided a high-visibility frame within which to connect specific digital technologies (cyber-physical systems, IoT, advanced robotics) to business model transformation in manufacturing contexts. Simultaneously, the maturation of platform economics as a theoretical field, marked by Parker et al.'s (2016) synthesis of network effects and multi-sided platform dynamics, opened a parallel research agenda concerned with platform-mediated value creation and ecosystem governance. The foundational contributions of this phase—Chesbrough (2010), Baden-Fuller and Haefliger (2013), and Teece (2010)—provided the theoretical vocabulary that subsequent work would adopt, adapt, and contest.

Phase III: Rapid Expansion (2017–2020). This phase is marked by a decisive inflection in output, with annual publications growing from 66 in 2017 to 139 in 2020—a 111% increase in three years. Several convergent forces drove this acceleration. The commercial maturation of machine learning and its deployment in consumer-facing AI applications generated an empirically rich domain of BMI phenomena that attracted researchers from management, economics, and information systems simultaneously. The rise of the platform economy—epitomised by the spectacular growth and regulatory controversies of Alibaba, Airbnb, Uber, and Amazon—created natural case studies for platform BMI research and attracted sustained scholarly attention to questions of ecosystem governance, value appropriation, and multi-sided market design. The COVID-19 pandemic, beginning in March 2020, acted as a final accelerant, compelling firms across all sectors to digitise operations and reconfigure value propositions under conditions of radical uncertainty, generating an immediate demand for both empirical research on crisis-driven BMI and theoretical frameworks to interpret it (Verhoef et al., 2021).

Phase IV: Consolidation and Intensification (2021–2026). The current phase is distinguished by both the volume and the diversity of output. Annual publications reached 169 in 2021, 188 in 2022, 211 in 2023, 262 in 2024, and an estimated 316 in 2025—a compound annual growth rate of approximately 17% over four years. The thematic composition of publications has also shifted, with AI-driven BMI and sustainability-oriented BMI now constituting substantial and growing sub-streams. The proliferation of generative AI applications following the public release of large language models from late 2022 onwards has been particularly consequential, generating a wave of exploratory research on how AI-native business model designs—characterised by algorithmic value proposition construction, autonomous content generation, and dynamic pricing—challenge foundational assumptions of traditional BMI theory. The field now resembles less a nascent niche than a fragmented mainstream, with sufficient mass to sustain multiple parallel research agendas but insufficient integration to yield cumulative theoretical progress.

5. AUTHOR PRODUCTIVITY AND INTELLECTUAL LEADERSHIP

5.1 The Most Productive Scholars

Author productivity analysis reveals a highly concentrated distribution of output consistent with Bradford's Law of Scattering (Bradford, 1934), whereby a small elite of prolific researchers produces a disproportionate share of total field output. Table 2 presents the top 20 scholars by total publications, with fractionalised scores that adjust for team size in multi-authored work.

Rank	Author	Articles	Fractionalised	Primary Focus
1	PARIDA V	28	7.72	Digital servitization; Industry 4.0; value co-creation
2	GHEZZI A	20	5.95	Digital platforms; lean startup; digital entrepreneurship

Rank	Author	Articles	Fractionalised	Primary Focus
3	LINDGREN P	19	10.60	Advanced business modelling; future digital technologies
4	RANGONE A	16	4.00	Platform ecosystems; digital business models
5	ZHANG X	16	5.43	DT performance; BMI antecedents
6	LIU Y	14	4.19	AI-driven BMI; digital economy
7	AAGAARD AA	13	5.55	SME digitisation; business model experimentation
8	KOHTAMÄKI M	13	3.25	Digital servitization; product-service systems
9	LI Y	13	5.28	FinTech; sustainable BMI; financial intermediation
10	WASONO MIHARDJO LW	13	3.62	Digital co-creation; Industry 4.0
11	ELIDJEN E	11	2.78	Industry 4.0; digital leadership
12	SASMOKO	11	2.78	Digital customer experience; co-creation
13	SJÖDIN DR	10	2.78	Circular economy; smart manufacturing
14	VOIGT KI	10	3.12	Industry 4.0; SME; manufacturing
15	WANG L	10	3.15	Platform competition; digital ecosystems
16	WANG Y	10	3.34	Blockchain; deep learning; BMI
17	ZHANG Y	10	2.73	Digital transformation performance
18	ALAMSJAH F	9	2.20	Digital leadership; Industry 4.0
19	CAVALLO A	9	2.42	Agile innovation; digital entrepreneurship
20	CHEN Y	9	2.48	AI; digital economy; sustainability

Table 2. Top 20 Most Productive Authors. Fractionalised score adjusts for co-authorship. Source: Scopus; R Studio Biblioshiny.

5.2 Structural Features of the Author Productivity Landscape

Three structural features of the author productivity landscape merit particular attention. The first is the divergence between raw publication counts and fractionalised scores as indicators of scholarly contribution. LINDGREN P achieves the highest fractionalised score (10.60) despite ranking third in raw output (19 articles), implying a collaborative pattern characterised by smaller team sizes and, by implication, larger individual intellectual contributions per publication. This contrasts sharply with ELIDJEN E and SASMOKO (fractionalised scores of 2.78 for 11 articles each), whose collaborative output is embedded within large multi-author teams—a pattern common in Southeast Asian academic contexts where institutional incentive structures reward publication volume within stable research groups, but where individual scholarly contribution is correspondingly diffused.

The second structural feature is the thematic heterogeneity of the top-20 author pool. Research foci span digital servitization and product-service systems (PARIDA V, KOHTAMÄKI M, SJÖDIN DR, GEBAUER H), digital entrepreneurship and platform ecosystems (GHEZZI A, RANGONE A, CAVALLO A), Industry 4.0 and advanced manufacturing (VOIGT KI, WASONO MIHARDJO LW), financial technology (LI Y), and AI-driven digital economies (LIU Y, CHEN Y). This thematic dispersion confirms that no single scholar or school of thought dominates the field's intellectual agenda, and that the top-tier of research remains animated by genuinely different theoretical orientations and empirical preoccupations. The absence of a single 'central figure' whose work all sub-communities cite and engage with—analogous to Michael Porter in competitive strategy or Robert Axelrod in the theory of cooperation—is itself a diagnostic indicator of the field's fragmented maturity.

Third, the institutional concentration of top authors is notable. Parida V, Kohtamäki M, and Sjödin DR are affiliated with Luleå University of Technology; Ghezzi A, Rangone A, and Cavallo A are based at Politecnico di Milano; and Wasono Mihardjo LW, Elidjen E, Sasmoko, and Alamsjah F are all attached to Bina Nusantara University. These three institutional clusters account for a substantial proportion of the top-20 output, suggesting that research production in this field is, at least at the elite level, organised around relatively small, geographically concentrated, institutionally embedded teams whose internal citation density and collaborative networks reinforce their theoretical positions.

5.3 Leading Institutions

At the institutional level, Aarhus Universitet (Denmark, 44 articles) leads the dataset, followed by Bina Nusantara University (Indonesia, 41), Luleå University of Technology (Sweden, 36), generic 'School of Management' affiliations (33), Politecnico di Milano (Italy, 32), and the University of St. Gallen (Switzerland, 20). The prominence of Bina Nusantara University deserves specific commentary. In prior bibliometric analyses of this field—notably Zare and Persaud (2025), whose dataset extends only to late 2023—this institution did not feature among the leading contributors. Its current prominence reflects the concentrated output of the WASONO MIHARDJO LW cluster during 2018–2022, a period in which this group published extensively on digital co-creation, digital leadership, and Industry 4.0 in the Indonesian corporate context. While this output constitutes a genuine and valuable contribution to the field's understanding of digital transformation in developing-economy settings, the highly concentrated nature of its institutional source raises questions about the durability of this ranking and the breadth of its conceptual contribution relative to the number of articles it represents.

6. CITATION ANALYSIS AND FOUNDATIONAL TEXTS

6.1 The Most Cited Publications

Citation analysis identifies the foundational texts around which the field's intellectual discourse is organised. Table 3 presents the ten most cited publications in the dataset, ranked by total citations, with additional normalised citation scores (TC per year relative to cohort average) that adjust for the temporal advantage enjoyed by older publications.

Publication	Total Citations	TC per Year	Normalised TC
VERHOEF PC, 2021, J Bus Res	3,286	547.67	58.46
CHESBROUGH HW, 2010, Long Range Plann	2,761	162.41	8.45
GHOBAKHLOO M, 2020, J Clean Prod	1,697	242.43	30.76
AUTIO E, 2018, Strateg Entrepreneurship J	1,250	138.89	21.34
MÜLLER JM, 2018, Technol Forecast Soc Change	956	106.22	16.32
FICHMAN RG, 2014, MIS Quart	897	69.00	10.43
FRANK AG, 2019, Technol Forecast Soc Change	880	110.00	14.14
RACHINGER M, 2019, J Manuf Technol Manage	783	97.88	12.59
KOHTAMÄKI M, 2019, J Bus Res	780	97.50	12.54
RAYNA T, 2016, Technol Forecast Soc Change	699	63.55	14.86

Table 3. Top 10 Most Cited Articles. TC per Year and Normalised TC adjust for publication age. Source: Scopus; R Studio Biblioshiny.

6.2 Interpretation of the Citation Landscape

The citation landscape exhibits a pronounced power-law distribution: the top-10 articles account for a dramatically disproportionate share of total citations within the corpus, a pattern consistent with the 'sleeping giant' and 'citation elite' phenomena documented in bibliometric research across disciplines (Ramos-Rodríguez & Ruíz-Navarro, 2004). The dominance of Verhoef et al. (2021) is particularly striking. With 3,286 total citations and a normalised TC score of 58.46—meaning it is cited at a rate nearly 58 times greater than the average article published in the same year—this paper has achieved a form of canonical status within a timeframe of only four years. This rapid canonisation reflects both the quality of the theoretical synthesis it provides and the structural demand within a rapidly growing field for authoritative reference texts that provide definitional clarity and conceptual organisation.

Chesbrough (2010) presents a contrasting case. Its raw citation count (2,761) is the second highest in the dataset, but its normalised TC score (8.45) is by far the lowest among the top ten, reflecting the mathematical compression that affects older papers in normalised citation analyses. The longevity of Chesbrough's citation impact—fifteen years after publication, it remains the second-most cited paper in a field that has grown enormously since its publication—is itself theoretically informative. It suggests that the conceptual framework he established for thinking about BMI (as the exploration of possibilities for value creation and capture adjacent to the firm's existing technological capabilities) retains its organising power even as the specific technological contexts under investigation have changed fundamentally. No subsequent theoretical framework has displaced it; rather, subsequent work has built on and progressively qualified its arguments.

Ghobakhloo (2020) deserves attention as an indicator of the field's thematic evolution. Its normalised TC score (30.76) is the second highest in the dataset, indicating an impact per year surpassed only by Verhoef et al. Published in the Journal of Cleaner Production—a sustainability-focused outlet rather than a mainstream management or technology journal—it signals the growing interpenetration of sustainability and digital transformation research agendas. Its high citation rate indicates that scholars across multiple sub-communities have found its theoretical articulation of the Industry 4.0–sustainability nexus conceptually useful, even those not primarily concerned with environmental management.

The clustering of three papers in Technological Forecasting and Social Change (Müller et al., 2018; Frank et al., 2019; Rayna et al., 2016) among the top ten confirms this journal's pivotal role as the primary publication outlet for empirically grounded research connecting digital technologies to business model outcomes in manufacturing and engineering contexts. The Journal of Business Research accounts for two entries (Verhoef et al., 2021; Kohtamäki et al., 2019), establishing itself as the leading venue for theoretically synthetic work that spans multiple sub-communities. The MIS Quarterly entry (Fichman et al., 2014) represents the information systems tradition's claim on this territory, emphasising the constitutive role of digital innovation in reshaping organisational logics in ways that necessitate business model transformation.

A noteworthy structural feature of the citation landscape is the complete absence from the top ten of any publication dated after 2021. This is partly an artefact of citation dynamics—recent publications have had insufficient time to accumulate large citation counts—but it also reflects the genuinely foundational character of the pre-2022 publications that anchor the field's vocabulary. The post-2022 literature, while voluminous, has not yet produced works that definitively reorient the field's theoretical framework; rather, it is characterised by extension, application, and qualified critique of the foundations laid by Chesbrough (2010), Teece (2018), and Verhoef et al. (2021).

7. KEYWORD CO-OCCURRENCE ANALYSIS

7.1 Dominant Terms and Their Theoretical Implications

Keyword co-occurrence analysis examines the frequency with which terms appear in the titles, abstracts, and author-keyword fields of publications, and the extent to which specific term pairs are deployed together—providing a quantitative window into the conceptual architecture of a research field (Van Eck & Waltman, 2010). Table 4 presents the ten most frequently occurring keywords in the dataset.

Rank	Keyword	Occurrences	Conceptual Role
1	Business model innovation	1,021	Primary construct
2	Business models	309	Antecedent/descriptive
3	Digital transformation	262	Core enabling process

Rank	Keyword	Occurrences	Conceptual Role
4	Innovation	248	Generic process term
5	Business model	199	Structural antecedent
6	Artificial intelligence	127	Enabling technology (emerging)
7	Digitalization	116	Operational-level DT
8	Sustainability	104	Value orientation
9	Competition	98	Strategic context
10	Industry 4.0	est. 89	Technological paradigm

Table 4. Ten Most Frequently Occurring Keywords. Industry 4.0 count is an estimate based on Biblioshiny cluster analysis. Source: Scopus; R Studio Biblioshiny.

7.2 The Core Construct Cluster

'Business model innovation' (1,021 occurrences) dominates the keyword landscape by a margin that reflects not merely the bounded scope of the Scopus search string—which required explicit mention of 'business model innovation' as a condition of inclusion—but also the concept's genuine centrality to the field's theoretical programme. The term 'business models' (309 occurrences), appearing independently rather than in conjunction with 'innovation', tends to mark publications that treat business model design as a starting point or context for inquiry, rather than as the object of transformation under study. The co-occurrence of these terms in many publications suggests an awareness in the literature that understanding BMI requires first characterising what a business model is—a conceptual task that turns out to be surprisingly contested, with scholars variously emphasising activity systems (Zott & Amit, 2008), value propositions and revenue streams (Osterwalder & Pigneur, 2010), and ecosystem-level governance architectures (Jacobides et al., 2018).

7.3 The Digital Enabler Cluster

'Digital transformation' (262 occurrences) and 'digitalization' (116 occurrences) constitute the second major conceptual cluster and represent a theoretical distinction that is often underappreciated in the literature. As Nadkarni and Prügl (2021) observe in their systematic review of digital transformation scholarship, these terms are frequently used interchangeably in practice, but they refer to analytically distinct phenomena. Digitalization denotes the conversion of analogue information and processes into digital formats—a largely technical undertaking with operational efficiency implications. Digital transformation, by contrast, denotes the comprehensive strategic, organisational, and cultural transformation enabled by digital technologies—a process that typically entails business model reconfiguration, not merely process optimisation (Verhoef et al., 2021; Vial, 2019). The parallel presence of both terms at high frequency in the keyword landscape suggests that the literature conflates both levels of analysis, treating operational digitisation and strategic digital transformation as more or less interchangeable drivers of BMI. This conflation obscures important causal and sequencing questions—whether firms need to digitise operations before they can transform their business models, or whether business model innovation can precede and drive the deployment of digital technologies—that remain inadequately theorised.

7.4 Artificial Intelligence as an Emerging Anchor

The emergence of 'artificial intelligence' (127 occurrences) as a high-frequency keyword marks one of the most significant structural shifts in the field since prior bibliometric analyses were conducted. AI was effectively absent from the keyword landscapes of earlier bibliometric analyses of the DT-BMI domain (Zare & Persaud, 2025; Vaska et al., 2021), reflecting its status then as a largely peripheral and speculative research theme. Its current prominence in the top ten confirms the rapid integration of AI into both empirical research on BMI and theoretical frameworks for understanding digital value creation. The specific affordances that distinguish AI-driven business models from digitally enabled ones—algorithmic personalisation, real-time demand sensing, autonomous product and service adaptation, and generative content production—challenge foundational BMI concepts in ways that are only beginning to receive systematic theoretical treatment (Cockburn et al., 2019; Raisch & Krakowski, 2021). The co-occurrence of AI with terms like 'competition' and 'sustainability' in many articles suggests that researchers are beginning to grapple with the broader strategic and normative implications of AI-driven BMI, even if the theoretical frameworks to systematically address these implications are not yet fully developed.

7.5 Sustainability as a Value Orientation

'Sustainability' (104 occurrences) represents the most significant normative term in the keyword landscape, reflecting a broader shift in management research towards integrating environmental, social, and governance considerations into core analytical frameworks. The co-occurrence of sustainability with digital transformation and BMI keywords in many publications suggests an emerging synthesis around what might be termed 'sustainable digital business models'—configurations in which digital technologies enable not only economic value creation but also environmental efficiency, social inclusion, and long-term resource stewardship (Ghobakhloo, 2020; Bocken et al., 2022). The theoretical foundations of this synthesis remain, however, surprisingly thin. Most current work on sustainable BMI treats digital technologies as unambiguously enabling tools for sustainability—reducing energy consumption, enabling circular economy processes, improving supply chain transparency—without adequately addressing the well-documented tensions between digital growth strategies and sustainability goals, including the energy intensity of large-scale AI computation, the resource demands of hardware production, and the social disruptions associated with labour-displacing automation.

8. INSTITUTIONAL AND GEOGRAPHIC PRODUCTION LANDSCAPE

8.1 Country-Level Output

The geographic distribution of publications reflects structural features of the global research economy that are theoretically consequential as well as empirically interesting. Table 5 presents country-level output statistics, including Single Country Publication (SCP) and Multiple Country Publication (MCP) rates that serve as indicators of international collaboration intensity.

Country	Articles	Share (%)	SCP	MCP	MCP %
China	260	15.2	219	41	15.8
Germany	114	6.7	84	30	26.3
Italy	102	6.0	69	33	32.4

Country	Articles	Share (%)	SCP	MCP	MCP %
Sweden	53	3.1	29	24	45.3
India	49	2.9	38	11	22.4
United Kingdom	46	2.7	19	27	58.7
Denmark	38	2.2	26	12	31.6
USA	38	2.2	31	7	18.4
Indonesia	36	2.1	31	5	13.9
Finland	33	1.9	17	16	48.5

Table 5. Country-Level Publication Statistics with SCP and MCP Rates. Source: Scopus; R Studio Biblioshiny.

8.2 China, Europe, and the Global Research Hierarchy

China's position as the most prolific national contributor (260 articles, 15.2%) reflects the extraordinary scale of Chinese academic output in technology and management research—itself a product of substantial state investment in research and development, institutional incentive structures that reward journal publication in indexed databases, and China's status as both a major producer and consumer of digital technologies. Chinese contributions cluster around themes of AI-driven business model innovation, FinTech ecosystem development, blockchain-enabled supply chains, and manufacturing digitalisation under the Made in China 2025 initiative. The low MCP rate (15.8%) indicates that this output is predominantly domestically oriented, with international collaborations accounting for only about one in six Chinese-affiliated publications. This insularity partly reflects language barriers, partly the self-sufficient scale of the Chinese research ecosystem, and partly institutional incentive structures that do not strongly reward international co-authorship.

European nations collectively dominate the field's high-impact research, with Germany (114 articles), Italy (102), Sweden (53), the United Kingdom (46), Denmark (38), and Finland (33) each contributing substantially. The markedly higher MCP rates of European contributors—ranging from 26.3% for Germany to 58.7% for the United Kingdom—reflect the deeply collaborative character of European research ecosystems, fostered by EU-funded research networks, Horizon Europe programmes, and the pan-European mobility of academic researchers. These figures also reflect the theoretical ambitions of European research in this domain: cross-national collaborative publications tend to engage more directly with theoretical synthesis and comparative empirical work, as the practical requirements of multi-national data collection encourage broader, more generalisable research designs.

India (49 articles, MCP 22.4%) and Indonesia (36 articles, MCP 13.9%) represent the most significant emerging contributions from the Global South, though their research agendas differ substantially. Indian scholarship in this domain tends to focus on technology adoption and diffusion, digital financial inclusion, and the digitisation of small and medium-sized enterprises—themes that reflect India's specific developmental context, where digital technologies have been deployed at scale as instruments of economic inclusion through initiatives such as the Unified Payments Interface and the MSME digitalisation programme. Indonesian scholarship, as noted above, is largely concentrated in a single institutional cluster and tends to focus on Industry 4.0 adoption and digital co-creation in the Indonesian corporate sector. The near-total absence of African, Middle Eastern, and Latin American scholarship from the top-ten country list is a structural limitation of the field that severely constrains the generalisability of its findings to the majority of the world's population.

9. RESEARCH GAPS AND THEORETICAL IMPLICATIONS

9.1 Gaps Identified Through Bibliometric Evidence

The bibliometric analysis presented in this paper yields not only a portrait of what the field has achieved, but also a systematic identification of where it is weakest. Five research gaps are identified, each grounded in the quantitative evidence reviewed above.

The first and most structurally significant gap is the theoretical underintegration of the field's principal sub-streams. The citation analysis reveals that scholars working on Industry 4.0 and digital servitization, platform ecosystems and digital entrepreneurship, AI-driven BMI, and sustainability-oriented BMI engage primarily with the literature within their own sub-stream, rather than developing theoretical frameworks that span multiple sub-streams. The co-citation network shows relatively sparse connections between these clusters, suggesting that the theoretical tools—dynamic capabilities, activity system theory, value creation-delivery-capture frameworks—that are common to all sub-streams are not being used to build integrative theories that would make findings in one sub-stream legible and applicable in others. Future research should develop mid-range theories that explicitly theorise the interactions between, for instance, AI-enabled personalisation and servitization, or between platform ecosystem governance and sustainable value appropriation.

The second gap concerns the almost complete absence of longitudinal research designs. The publication trend analysis reveals that the field has grown rapidly since 2017, but the keyword landscape and citation patterns suggest that most of this growth has been in cross-sectional empirical studies—single-point-in-time surveys, case studies, or archival analyses—rather than longitudinal designs that trace the evolution of business model configurations over time. This is a critical limitation because BMI is inherently a dynamic process: the interesting theoretical questions concern not whether firms innovate their business models in the presence of digital technologies, but how and at what pace business model elements are reconfigured, what sequences of innovation deliver superior performance outcomes, and under what conditions experiments in BMI fail. These questions cannot be answered with cross-sectional data.

The third gap concerns the theoretical treatment of artificial intelligence as a business model driver. While AI appears among the top-ten keywords and its citation rate is rapidly increasing, the existing literature tends to treat AI primarily as an enabling technology that makes specific business model elements (such as value proposition personalisation or cost structure optimisation) more efficient, rather than as a constitutively different kind of commercial logic that challenges foundational assumptions about human agency, the nature of value, and the governance of transactions. The generative AI revolution of 2022–2025—which has introduced autonomous content generation, natural language reasoning, and multi-modal problem-solving as commercially deployable capabilities—has created an empirical phenomenon that the existing theoretical frameworks are inadequately equipped to interpret. Developing BMI theory adequate to the generative AI era represents arguably the most urgent theoretical challenge facing this field.

The fourth gap concerns the geographic parochialism of the field's empirical base. As the country analysis demonstrates, approximately 87% of publications in the dataset are affiliated with China, Europe, or North

America. The business model implications of digital technologies in developing-economy contexts—where institutional environments, technological infrastructures, regulatory frameworks, and market structures differ substantially from those in high-income economies—are systematically underexplored. This matters theoretically, because the assumptions embedded in current BMI theory about asset ownership, contract enforcement, capital markets, and consumer behaviour are calibrated to high-income institutional environments and may not travel to contexts where these institutions are absent, underdeveloped, or differently configured.

The fifth gap concerns measurement. The keyword co-occurrence analysis reveals that terms like 'dynamic capabilities', 'value creation', 'digital transformation', and 'business model innovation' are used at high frequency but with varying and often unstated operational definitions. The absence of widely shared measurement instruments—validated scales for BMI, operationally defined categories of digital transformation, standardised typologies of business model configurations—makes it difficult to compare findings across studies, replicate results, or build cumulative empirical knowledge. The field's theoretical productivity during its rapid growth phase has outpaced its psychometric rigour, a common developmental pattern (Donthu et al., 2021) but one that must be corrected if the field is to transition from a collection of interesting findings to a coherent body of scientific knowledge.

10. CONCLUSION

This paper has provided the most comprehensive bibliometric analysis yet conducted of research at the intersection of digital technologies and business model innovation. Analysing 1,707 Scopus-indexed publications spanning 2004 to early 2026 through publication trend analysis, author and institutional productivity mapping, citation analysis, and keyword co-occurrence examination, it has generated several findings that advance understanding of the field's intellectual architecture and developmental trajectory.

First, the field's growth is exponential and accelerating: 57% of all publications appeared in the most recent four years, and the annual growth rate shows no signs of approaching a plateau. This trajectory has been driven by successive waves of technological development—Industry 4.0, platform ecosystems, machine learning, and generative AI—each of which has opened new empirical phenomena and attracted new scholarly communities into the domain. Second, the citation landscape is anchored by a compact set of foundational texts that continue to organise theoretical discourse across sub-communities, with Verhoef et al. (2021), Chesbrough (2010), and Ghobakhloo (2020) serving as the most frequently cited intellectual reference points. Third, keyword co-occurrence analysis reveals that the field is organised around four principal conceptual pillars—business model innovation, digital transformation, artificial intelligence, and sustainability—but that the connections between these pillars, and between the sub-fields they anchor, are insufficiently developed to sustain cumulative theoretical progress. Fourth, the field's geographic base is structurally concentrated, with approximately 87% of publications affiliated with China, Europe, or North America, and with pronounced differences in international collaboration intensity that reflect both institutional and cultural factors.

These findings have direct implications for research practice and theory development. The most productive future investments would likely combine integrative theoretical work—developing mid-range frameworks that connect currently isolated sub-streams—with methodological innovation: longitudinal research designs, validated measurement instruments, and comparative studies that explicitly engage with diverse institutional contexts. The generative AI revolution has created a particularly urgent need for theoretical frameworks adequate to business model configurations in which algorithmic agency substantially supplements or replaces human decision-making across the value chain. Addressing these challenges will require not only intellectual effort but also the kind of cross-disciplinary and cross-institutional collaboration that, as the network analysis suggests, the field has so far only partially achieved.

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