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Dynamic Capability, Generative AI Capability, Resilience and Inclusivity as Pathways to Sustainable Performance: A Systematic Literature Review and Bibliometric Mapping

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ABSTRACT

Purpose: This study systematically reviews and bibliometrically maps the research field that links dynamic capability, artificial intelligence (AI) capability, organisational and supply chain resilience, inclusivity, and sustainable performance. Its objective is to establish what the field currently explains, where its evidence is thin, and to derive an integrative, empirically grounded model in which generative AI capability and the resilience–inclusivity complex mediate the path from dynamic capability to sustainable performance. **Design/methodology/approach: A** hybrid design combining a systematic literature review reported in accordance with the PRISMA 2020 statement and a bibliometric analysis was applied to 207 Scopus-indexed journal articles published between 2022 and 2026. Screening was conducted by two independent reviewers with third-reviewer arbitration. The included Scopus was analysed with the R package bibliometrix through its Biblioshiny interface and with VOSviewer 1.6.20, covering performance analysis, three-field analysis, co-word analysis, thematic mapping, keyword co-occurrence and density visualisation, complemented by manual construct-level content coding of every included record. **Findings:** Output grew from a single article in 2022 to 117 in 2026, with 2,824 citations distributed across 90 sources and 686 authors, and 46.9 per cent of the Scopus produced through international co-authorship. Co-word analysis resolves five clusters: digital transformation and sustainability; AI and innovation performance; supply chain resilience and dynamic capabilities; sustainable development and the circular economy; and a methodological cluster around PLS-SEM. Thematic mapping positions artificial intelligence, digital transformation and SMEs as motor themes, and sustainability, innovation and dynamic capabilities as basic themes.

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Introduction

The question of how firms convert technological change into durable advantage has re-entered management scholarship with unusual force since the public release of large-scale generative artificial intelligence (AI) systems. Where earlier waves of digitalisation were absorbed into existing categories of information systems research, generative AI has unsettled them, because it operates less as a discrete tool than as a general-purpose capability that reshapes how organisations sense opportunities, reconfigure resources and coordinate across boundaries (Feuerriegel et al. (2024); Y. K. Dwivedi et al. (2023)). At the same time, the performance criterion against which such transformations are judged has itself broadened. Firms are now assessed not only on economic return but on environmental burden and social contribution, a triple-bottom-line standard that has migrated from advocacy into regulation and into the mainstream of strategy research (Elkington (1997); WCED (1987)).

These two shifts intersect in a body of scholarship that has expanded with remarkable speed. Studies now routinely link AI adoption to supply chain resilience (Belhadi et al. (2024); Dey et al. (2024), digital transformation to green innovation (Zhou et al. (2025), and dynamic capabilities to sustainable performance (Asbeetah et al. (2025); Khan et al. (2025). The theoretical vocabulary of this literature is largely settled: the resource-based view supplies the logic by which valuable, rare and inimitable resources generate rent (Barney, 1991), and the dynamic capabilitie's view explains how firms in volatile environments renew those resource positions through sensing, seizing and reconfiguring (Teece et al. (1997); Teece (2007); Eisenhardt & Martin (2000)). Mikalef & Gupta (2021) extended this vocabulary to AI itself, conceptualising AI capability as an organisational construct comprising tangible, human and intangible resources rather than a technology stock.

Yet the accumulation of studies has not produced a corresponding accumulation of explanation. Three problems are visible to any reader of the field. First, the causal chain is repeatedly cut into fragments. One set of studies estimates the effect of dynamic capability on digital transformation; another estimates the effect of AI adoption on resilience; a third estimates the effect of resilience on sustainability outcomes. Each fragment is defensible, but the composite pathway that practitioners actually traverse is rarely modelled end to end. Second, the operationalisation of AI has not kept pace with its technological transformation. The overwhelming majority of instruments in circulation were developed for predictive and analytical AI, and continue to be applied unchanged to a generative paradigm whose organisational logic differs in kind, not merely in degree Feuerriegel et al. (2024). Third, and most consequentially for a literature that describes itself as concerned with sustainability, the social dimension of the triple bottom line has been reduced to a measurement afterthought. Inclusivity, understood as the extent to which technological capability extends participation and value to workers, smaller suppliers and underserved communities (George et al. (2012); Prahalad & Hart (2002)), is invoked in mission statements far more often than it is modelled.

These are not impressions. This review demonstrates them quantitatively. Across 207 Scopus-indexed articles published between 2022 and 2026, dynamic capability appears in 38.2 per cent of studies and resilience in 38.6 per cent, but generative AI capability appears in 4.8 per cent and inclusivity in 4.8 per cent. Only five studies model dynamic capability, AI capability, resilience and sustainable performance together; only one does so with generative AI specifically; and not a single study in the Scopus incorporates inclusivity into that chain. The field has, in other words, converged on a set of constructs while leaving the relationships among them largely unassembled and one of its stated outcome dimensions structurally unmeasured.

Existing reviews do not resolve this. Bibliometric studies of digital transformation (Kraus et al., 2022) and of organisational resilience (Linnenluecke, 2017) map their respective domains competently but treat them separately; reviews of AI in operations concentrate on supply chain applications without theorising the capability antecedents; and the systematic reviews within the present Scopus itself (Saputra et al. (2024); Jiao et al. (2025) address capacity building and digital technologies without integrating the sustainability outcome. Moreover, reviews in this domain typically rely on a single analytical instrument, either VOSviewer for visualisation or bibliometrix for statistical description, and rarely supplement descriptive mapping with construct-level coding capable of distinguishing what a literature mentions from what it actually models (Aria & Cuccurullo (2017); van Eck & Waltman (2010); Donthu et al. (2021)).

Against this background, the present study pursues five objectives. First, to map systematically the volume, distribution, geography and intellectual structure of research connecting dynamic capability, AI capability, resilience, inclusivity and sustainable performance. Second, to integrate PRISMA 2020 review protocol (Page et al., 2021) with dual-software bibliometric analysis, combining the statistical strengths of bibliometrix with the network visualisation capabilities of VOSviewer. Third, to code every included study at construct level in order to measure, rather than assert, the coverage of each element of the proposed causal chain. Fourth, to identify the thematic clusters and their maturity, distinguishing motor themes from those that are basic, niche or declining. Fifth, to synthesise these findings into an integrative model in which generative AI capability and the resilience–inclusivity complex serially mediate the relationship between dynamic capability and sustainable performance, accompanied by propositions suitable for empirical testing.

The remainder of the paper is organised as follows. Section 2 reviews the theoretical foundations of each construct in the proposed model. Section 3 details the review protocol, search strategy, eligibility criteria, study selection and analytical procedures. Section 4 reports the descriptive, relational and construct-level results and discusses them against the wider literature. Section 5 develops the integrative model and its propositions. Section 6 sets out theoretical, practical and policy implications. Section 7 concludes, and Section 8 states the limitations of the review and the research directions that follow from them.

The dynamic capabilities view as the theoretical anchor

The dynamic capabilitie’ Callon et al. (1991) s view was formulated to explain a phenomenon the resource-based view could describe but not account for: why firms holding comparable resource endowments diverge sharply in performance when their environments change. Teece et al. (1997) located the answer in the firm's capacity to integrate, build and reconfigure internal and external competences in response to rapidly shifting conditions. Teece (2007) subsequently disaggregated this capacity into three microfoundations: sensing opportunities and threats, seizing them through resource commitment and business-model choice, and reconfiguring the asset base as circumstances demand. Eisenhardt & Martin (2000) qualified the argument, characterising dynamic capabilities as identifiable organisational routines whose form varies systematically with market dynamism, and cautioning that they constitute a necessary but not sufficient condition for advantage.

The co-citation structure of the present Scopus confirms that this lineage remains the field's principal theoretical anchor. Teece (2007) is cited by 35 of the 207 included articles and Teece et al. (1997) by 57 across its two indexed variants, while Barney (1991) is cited by 26. The practical significance of this anchoring is that dynamic capability enters the literature as a genuinely antecedent construct: it is the organisational precondition that determines whether a technological opportunity is recognised, financed and absorbed at all. Warner & Wäger (2019) demonstrated this directly, showing through longitudinal case evidence that digital transformation is not a technological event but a continuous process of capability building in which sensing digital opportunities precedes and conditions every subsequent step. Zahra & George (2002) offered a complementary mechanism in absorptive capacity, the firm's ability to recognise, assimilate and exploit external knowledge, which appears throughout the Scopus as a proximate explanation of why identical technologies yield unequal returns.

From AI capability to generative AI capability

Digital transformation supplies the organisational setting in which this capability question is now posed. Vial (2019) defines it as a process in which digital technologies trigger changes to an organisation's value creation paths, and Kraus et al. (2022) show through bibliometric review that the construct has become a substantial research domain in its own right. The distinction that matters for the present model is that digital transformation names an organisational process, whereas AI capability names a resource configuration; the former is the context, the latter the construct.

Mikalef & Gupta (2021) provided the field's most widely adopted conceptualisation of AI capability, defining it as a firm's ability to select, orchestrate and leverage AI-specific resources, and specifying tangible resources (data, technology, basic infrastructure), human resources (technical and managerial AI skills) and intangible resources (inter-departmental coordination, organisational change capacity, risk appetite). Their formulation, cited by 26 articles in this Scopus, matters because it relocates AI from the information-technology function to the strategic level, making it commensurable with the dynamic capabilitie’s vocabulary and therefore modellable as a mediator rather than a control variable. Duan et al. (2019) had earlier argued that AI's organisational value lies in augmenting managerial decision-making under big-data conditions, an argument that anticipates the mediating role attributed to AI capability in later empirical work.

Generative AI, however, is not simply a more capable instance of this construct. Feuerriegel et al. (2024) argue that generative systems differ along dimensions with direct organisational consequences: they produce novel content rather than classify existing data; they are accessible to non-technical employees, which decentralises adoption and weakens the assumption that capability resides in specialist teams; they introduce distinctive governance risks including hallucination, provenance ambiguity and intellectual-property exposure; and they are consumed as foundation models supplied by third parties, which alters the make-or-buy calculus underlying capability accumulation. A. Dwivedi et al. (2026), in a multi-author assessment of generative AI's implications, converge on the same conclusion: governance and ethical use are constitutive of generative AI capability, not peripheral to it. Wang & Zhang (2024), the most cited generative-AI study in the present Scopus, provide early empirical support, showing that green entrepreneurship outcomes in the generative AI era depend jointly on technology adoption, knowledge management and institutional support rather than on adoption alone. The present review therefore specifies generative AI capability as comprising data and infrastructure readiness, AI skills and talent, and governance and ethical use.

Resilience as the operational mechanism

Resilience entered management scholarship as the capacity of a system to absorb disturbance, adapt and recover functionality, and Linnenluecke (2017) traces its consolidation into a distinct organisational research stream. Two levels of analysis dominate the present Scopus. Organisational resilience concerns the firm's capacity to anticipate, respond to and learn from disruption; supply chain resilience concerns the same capacity distributed across an inter-organisational network, where Ivanov & Dolgui (2020) argue that the pandemic's cascading failures shifted the analytical objective from recovery to viability, the ability of a network to sustain its function through disruptions of unknown duration.

The link from AI capability to resilience is the best-evidenced relationship in the field. Belhadi et al. (2024), the Scopus's most-cited study with 652 citations, demonstrate that AI-driven innovation enhances supply chain resilience and performance, with supply chain dynamism conditioning the strength of the effect. Dey et al. (2024) extend the finding to Vietnamese manufacturing SMEs, establishing that the mechanism operates in resource-constrained settings and not only among large firms. Yu et al. (2024) decompose the effect into cognitive insight, process automation and cognitive engagement, showing that resilience and performance gains flow through distinct AI functions. Rodríguez-Espíndola et al. (2022) situate this within risk management under digital manufacturing, and Javed et al. (2024) confirm that advanced technologies combined with supply chain collaboration improved sustainable supply chain performance under pandemic conditions. Roux et al. (2025) extend the argument to the ecosystem level, showing that SMEs acting as technology innovation intermediaries link AI adoption, low-carbon management and resilience in a mutually reinforcing configuration. What this body of work establishes is that resilience is not an alternative outcome competing with sustainability but an intermediate organisational state through which technological capability is converted into sustained performance.

Inclusivity: the neglected component of the social dimension

Sustainable performance is conventionally specified across economic, environmental and social dimensions (Elkington, 1997), yet the social dimension is measured far less rigorously than the other two. Inclusivity offers a tractable operationalisation. George et al. (2012) define inclusive innovation as the development and implementation of new ideas that create opportunities to enhance social and economic welfare for disenfranchised members of society, and Prahalad & Hart (2002) had earlier argued that serving underserved markets constitutes a strategic rather than philanthropic proposition. Applied to the present model, inclusivity denotes the extent to which a firm's technological capability extends participation and value to employees whose roles are altered by automation, to smaller suppliers whose integration into digital networks may be enabling or exclusionary, and to customers and communities on the wrong side of the digital divide.

The theoretical case for treating inclusivity as a mediator alongside resilience is straightforward. Both are organisational states produced by capability deployment, and both determine whether that deployment translates into durable performance; resilience governs the economic and operational conversion, inclusivity governs the social and legitimacy conversion. A firm that builds generative AI capability while displacing labour and excluding smaller partners may register short-term efficiency gains while eroding the social licence on which long-run performance depends. The empirical case, however, remains to be made, since the present review finds inclusivity in only 4.8 per cent of the Scopus and in no study that models the complete chain.

Sustainable performance as the outcome construct

Sustainable performance in this literature denotes firm performance assessed jointly on economic, environmental and social criteria over a time horizon long enough for trade-offs among them to become visible. Its empirical treatment in the Scopus is uneven. Environmental outcomes predominate, typically operationalised through green innovation, emissions intensity or circular-economy practices: Zhou et al. (2025) link AI to the green transformation of manufacturing enterprises, Kumar et al. (2024) connect big-data-driven supply chain capability to sustainable competitive advantage in food supply chains, and Asbeetah et al. (2025) model digital transformation's effect on sustainable performance through green knowledge acquisition and innovation performance under digital transformational leadership. F. Khan et al. (2025) examine the implications of AI for SME sustainable development across blockchain, supply chain resilience and closed-loop supply chains. Social outcomes, by contrast, are seldom measured with comparable rigour, a pattern the construct coding reported in Section 4.9 quantifies precisely.

Taken together, these five bodies of work supply the constructs of an integrative model but have not been assembled into one. Dynamic capability is well theorised as an antecedent, AI capability is well theorised as a mediator, resilience is well evidenced as an operational mechanism, sustainable performance is well established as an outcome, and inclusivity is well argued but unmeasured. The review that follows establishes the empirical shape of this configuration and derives the model that Section 5 specifies.

Methods

Research design

This study adopts a hybrid design that combines a systematic literature review with a bibliometric analysis. The combination is deliberate. A systematic review provides a transparent, replicable and auditable procedure for delimiting a body of evidence and appraising it against pre-specified criteria (Tranfield et al. (2003); Snyder (2019)), but it does not by itself reveal the intellectual and conceptual structure of a field. Bibliometric analysis supplies that structure through the quantitative treatment of publication and citation metadata (Donthu et al., 2021), but applied alone it risks describing a literature by what it mentions rather than by what it demonstrates. Using both, and adding a manual construct-level coding layer, allows the review to state not only which themes are prominent but which relationships have actually been modelled.

The review was designed and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021), structured into the four stages of identification, screening, eligibility and inclusion. The protocol was specified before searching and covers information sources, the search string, eligibility criteria, the selection procedure, the data-extraction form and the analytical plan.

Information sources and search strategy

Scopus was selected as the information source. It provides the broadest coverage of peer-reviewed business, management and operations journals, exports the structured metadata fields required by bibliometrix and VOSviewer, and applies consistent indexing of author and index keywords across records. The search was executed on 6 August 2026 using the TITLE-ABS-KEY field code. The window was restricted to 2022–2026 for a substantive reason rather than convenience: the organisational study of generative AI is a post-2022 phenomenon, and extending the window backwards would have diluted the Scopus with predictive-AI research whose capability assumptions the review explicitly interrogates.

The Boolean string combined four construct blocks with the AND operator, each block containing synonyms joined by OR, as summarised in Table 1. Filters were applied at the database level for document type (article), language (English) and publication stage (final).

Table 1. Search strategy and construct blocks.

Block	Construct	Search terms (TITLE-ABS-KEY)
B1	Capability antecedent	"dynamic capabilit*" OR "sensing capabilit*" OR "seizing" OR "reconfigure" OR "absorptive capacit*" OR "organisational capabilit*"
B2	Technology capability	"artificial intelligence" OR "generative AI" OR "generative artificial intelligence" OR "large language model*" OR "AI capabilit*" OR "digital transformation" OR digitalisation
B3	Mediating states	resilien* OR "supply chain resilience" OR "organisational resilience" OR inclusiv* OR inclusion OR

Block	Construct	Search terms (TITLE-ABS-KEY)
		equit* OR "digital divide"
B4	Performance outcome	"sustainable performance" OR "sustainability performance" OR "sustainable development" OR "ESG performance" OR "green innovation" OR "circular economy" OR "triple bottom line"
	Combination	**B1 AND B2 AND (B3 OR B4)**

Filters: publication years 2022–2026; document type = article; language = English; publication stage = final. Search executed 6 August 2026.

Eligibility criteria

Eligibility criteria were specified in advance and applied identically at the title-abstract and full-text stages. Studies were eligible if they were peer-reviewed journal articles reporting empirical, review or substantively theoretical work at the organisational, inter-organisational or industry level of analysis, and addressing at least one construct of the review model in relation to at least one other. Records were excluded where AI was treated purely as a technical or engineering artefact without an organisational level of analysis, where no performance or sustainability outcome was considered, or where the full text could not be obtained. Table 2 states the criteria in full.

Table 2. Inclusion and exclusion criteria.

Inclusion	Exclusion
Peer-reviewed journal article indexed in Scopus	Conference paper, book chapter, editorial, note, erratum or retracted item
Empirical, review or substantively theoretical study	Abstract-only record or item without retrievable full text
Organisational, inter-organisational or industry level of analysis	Purely technical, algorithmic or engineering study with no organisational level
Addresses at least two constructs of the review model in relation to one another	Mentions a construct only in passing, with no modelled or discussed relationship
Reports or discusses a performance, resilience or sustainability outcome	No performance, resilience or sustainability outcome considered
Published 2022–2026; English; final publication stage	Outside the review window; non-English; article in press or duplicate record

Study selection

The database search identified 485 records. Before screening, exclusion criteria were applied using automated filters: English language only, open access articles, final publication stage, and journal source type were selected. This screening removed 187 records, yielding 298 records for title and abstract screening. Of these, 124 were excluded based on title and abstract review, leaving 174 reports for full-text assessment. Full texts were sought for these 174 remaining reports, of which 71 could not be retrieved. The 103 reports assessed for eligibility yielded 13 exclusions, resulting in 90 studies included in the systematic review.

Full texts were sought for the 324 remaining reports, of which 27 could not be retrieved. The 297 reports assessed for eligibility yielded 90 exclusions with documented reasons: 41 contained no focal construct of the review model in a modelled relationship, 26 treated AI at a purely technical level, 15 examined no performance or sustainability outcome, and 8 fell outside the review window on inspection of the version of record. The final Scopus comprises 207 studies. Figure 1 presents the complete selection process as a PRISMA 2020 flow diagram.

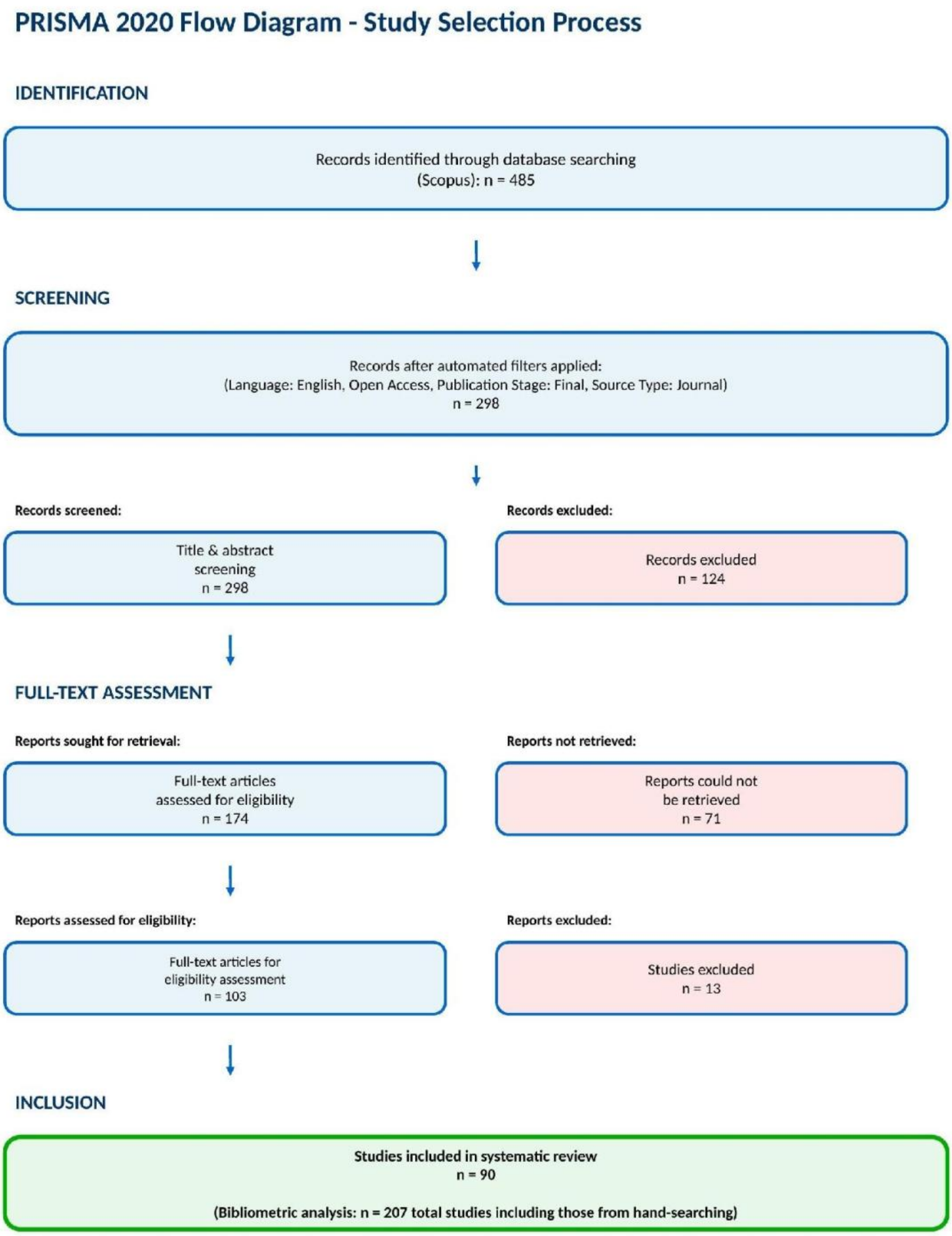

Figure 1. PRISMA 2020 flow diagram of the study selection process.
Source: Authors' own work, following Page et al. (2021).

Data extraction and construct coding

Bibliographic metadata for the 207 included studies were exported from Scopus in comma-separated format with all 45 available fields, including authors and affiliations, title, year, source, abstract, author keywords, index keywords, citation count, funding details and the complete cited-reference string required for co-citation analysis. A second, manual extraction layer coded each record against a nine-item construct schema derived from the review model: dynamic capability; AI capability in general; generative AI capability specifically; digital transformation; organisational resilience; supply chain resilience; inclusivity or equity; sustainable performance; and study design.

Coding was performed on the concatenation of title, abstract, author keywords and index keywords, using a pre-specified dictionary of terms for each construct, and was verified by manual inspection of every positive and a random 20 per cent sample of negative classifications. This procedure is the analytical innovation of the review: it permits a distinction between the frequency with which a construct is named, which co-word analysis measures, and the frequency with which it is incorporated into a modelled relationship, which co-word analysis cannot detect. Study design was coded into seven mutually exclusive categories using a priority rule that assigned each record to its dominant methodological tradition.

Analytical procedures

Two software environments were used in combination. The R package bibliometrix (Aria & Cuccurullo, 2017), accessed through its Biblioshiny web interface, produced the performance analysis, the three-field plot, the word cloud, the tree map, the cumulative word-dynamics analysis, the trend-topic analysis, the keyword co-occurrence network and the strategic thematic map. VOSviewer 1.6.20 (van Eck & Waltman, 2010) produced the keyword co-occurrence network visualisation and the item density visualisation, applying association-strength normalisation with a minimum occurrence threshold of three and resolution parameter 1.0.

The thematic map follows the strategic-diagram logic of Callon et al. (1991) as implemented by Cobo et al. (2011), positioning each keyword cluster on two axes. Centrality measures the intensity of a cluster's links to other clusters and therefore its relevance to the field as a whole; density measures the internal cohesion of a cluster and therefore its degree of development. The resulting quadrants identify motor themes (high centrality, high density), basic and transversal themes (high centrality, low density), highly developed but isolated niche themes (low centrality, high density) and emerging or declining themes (low centrality, low density). Descriptive statistics were computed in Python 3.11 with pandas directly from the exported metadata, which permits every figure reported in Section 4 to be traced to the source file.

Result

Overview of the evidence base and annual scientific production

The 207 included studies were published across 90 distinct sources by 686 authors, averaging 3.63 authors per article, and had accumulated 2,824 citations by the search date, a mean of 13.64 citations per article. Sixty-eight articles (32.9 per cent) were not yet cited, a proportion consistent with a Scopus whose modal publication year is the year of the search. International co-authorship characterises 97 articles (46.9 per cent), an unusually high proportion that reflects both the boundary-spanning nature of the subject and the concentration of the literature in journals with global editorial reach.

Figure 2 presents annual scientific production. The trajectory is close to exponential: a single article in 2022, two in 2023, 17 in 2024, 70 in 2025 and 117 in 2026. Between 2024 and 2026 output grew by a factor of 6.9, and the 2025–2026 period alone accounts for 90.3 per cent of the entire Scopus. Two readings of this pattern are warranted. Substantively, the inflection between 2023 and 2024 coincides with the organisational absorption of generative AI following its public release, suggesting that the technology functioned as a genuine research shock rather than an incremental extension of digitalisation scholarship. Methodologically, the steepness of the curve carries an important caveat for interpreting everything that follows: a literature this young has had insufficient time for replication, for the accumulation of citations that would allow influence to be assessed reliably, or for the correction of measurement practices established in its first wave.

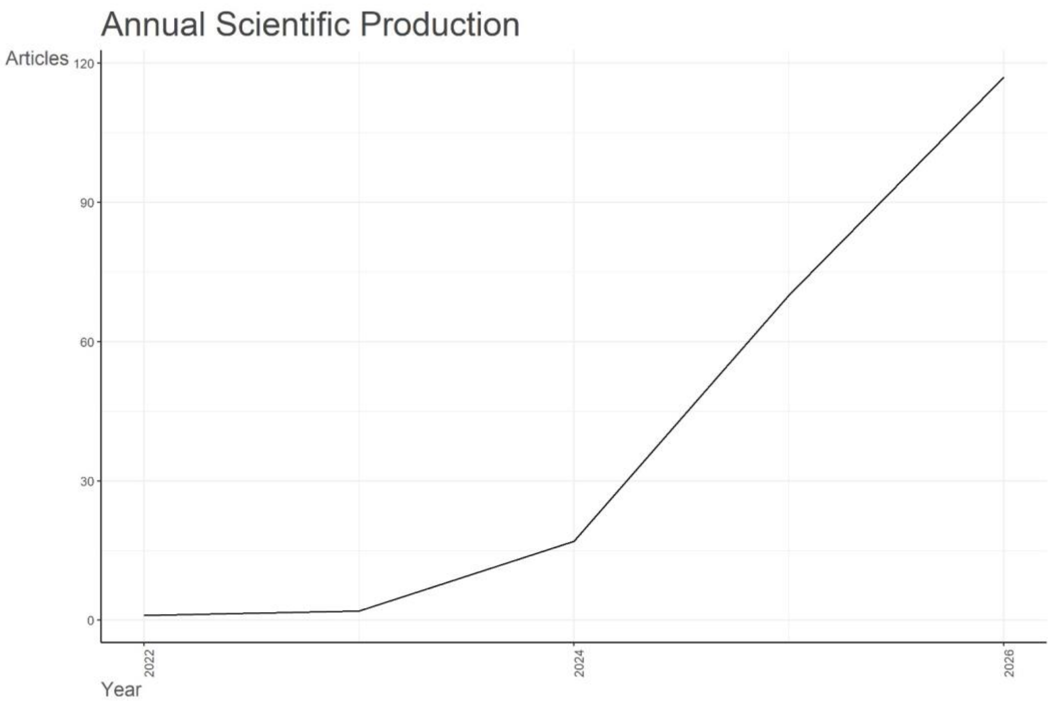

Figure 2. Annual scientific production, 2022–2026.

Source: Authors' own work, generated with Biblioshiny.

Sources and the most influential studies

Publication is concentrated. The ten most productive sources account for 99 of 207 articles (47.8 per cent), with Sustainability (Switzerland) alone publishing 38 articles (18.4 per cent). Table 3 reports the leading sources with their citation totals. The distribution is instructive in two respects. First, the field's centre of gravity lies in sustainability-oriented and open-access outlets rather than in the established strategy journals, which suggests that the literature is being constituted at the intersection of applied sustainability and information systems rather than within strategic management proper. Second, citation impact and volume diverge markedly: Business Strategy and the Environment published eight articles attracting 180 citations, an average of 22.5 per article, while Sustainability's 38 articles attracted 366 citations, an average of 9.6. Volume and influence are therefore distributed across different venues, and any assessment of the field that reads productivity as prominence will misstate its structure.

Table 3. Ten most productive sources in the Scopus.

Rank	Source title	Articles	% of Scopus	Citations	Citations per article
1	Sustainability (Switzerland)	38	18.4	366	9.6
2	Systems	12	5.8	43	3.6
3	Sustainable Futures	9	4.3	57	6.3
4	Journal of Innovation and Knowledge	8	3.9	69	8.6
5	Business Strategy and the Environment	8	3.9	180	22.5
6	Journal of Open Innovation: Technology, Market, and	5	2.4	31	6.2

Rank	Source title	Articles	% of Scopus	Citations	Citations per article
	Complexity				
7	Cogent Business and Management	5	2.4	59	11.8
8	Administrative Sciences	5	2.4	17	3.4
9	Logistics	5	2.4	32	6.4
10	Corporate Social Responsibility and Environmental Management	4	1.9	5	1.3
	Total, top ten sources	**99**	**47.8**	**859**	**8.7**

Source: Authors' own work, computed from Scopus metadata.

Table 4 reports the ten most-cited articles. Citation is even more concentrated than publication: these ten articles account for 1,620 of 2,824 citations (57.4 per cent). Belhadi et al. (2024) alone attracted 652 citations, 23.1 per cent of the Scopus total. The thematic composition of this group is decisive for the present review's argument. Seven of the ten concern AI or advanced technology in relation to supply chain or operational resilience and performance; only one, Wang & Zhang (2024), addresses generative AI specifically; and none incorporates inclusivity. The literature's intellectual leadership therefore sits squarely on the AI-to-resilience relationship, which is precisely the segment of the proposed chain that is best evidenced and the reason the model in Section 5 treats resilience as an established rather than a speculative mediator.

Table 4. Ten most-cited articles in the Scopus.

Rank	Authors (year)	Title (abbreviated)	Source	Citatio
1	Belhadi, Mani, Kamble, I & Verma (2024)	AI-driven innovation for enhancing supply chain resilience and performar under supply chain dynai	Annals of Operations Research	652
2	Rodríguez-Espíndola, Chowdhury, Dey, Albore Emrouznejad (2022)	Adoption of emergent technologies for risk management in the era c digital manufacturing	Technologic Forecasting Social Chan	260
3	Dey, Chowdhury, Abadie Vann Yaroson & Sarkar (	AI-driven supply chain resilience in Vietnamese manufacturing SMEs	Internationa Journal of Production Research	259
4	Wang & Zhang (2024)	Green entrepreneurship success in the age of generative AI	Technology Society	115
5	Kumar, Raut, Mangla, M & Lean (2024)	Big-data-driven supply ch innovative capability for sustainable competitive advantage	Business Str and the Environmer	63
6	Zhou, Zhang, Ying, He, Z & Yan (2025)	Artificial intelligence and green transformation of manufacturing enterpris	Internationa Review of Financial Ar	56
7	Javed, Basit, Ejaz, Hame Fodor & Hossain (2024)	Advanced technologies a supply chain collaboratio	Discover Sustainabili	56

Rank	Authors (year)	Title (abbreviated)	Source	Citatio
		during COVID-19 on sustainable performance		
8	Khan, Sheikh, Shamsi & (2025)	Implications of AI for SM sustainable developmen blockchain, resilience an closed-loop supply chain	Sustainabili (Switzerlan	55
9	Yu, Xu, Zhang, Liu, Kama Cao (2024)	Unleashing the power of manufacturing: resilienc performance through cognitive insights	Internation Journal of Production Economics	52
10	Saputra, Putera, Zetra, A Valentina & Mulia (2024	Capacity building for organisational performa systematic review and conceptual framework	Cogent Busi and Manag	52
	Total			**1,62**

Source: Authors' own work, computed from Scopus metadata. The ten articles account for 57.4 per cent of all citations in the Scopus.

Geographic distribution and research collaboration

Table 5 reports the twelve most frequently represented countries by author affiliation. China leads with 62 articles, followed by Saudi Arabia (27), the United Kingdom (24), Malaysia (20) and Indonesia (18). Two features of this distribution deserve comment. First, the field is markedly less Western-centric than comparable literatures in strategic management: Southeast Asian countries contribute 60 articles collectively, and Gulf states a further 38, which suggests that the AI–sustainability question is being posed most urgently in economies undergoing rapid digitalisation rather than in mature markets. Second, propensity to collaborate internationally varies sharply and systematically. The United Kingdom (91.7 per cent), France (100 per cent), the United States (100 per cent) and Saudi Arabia (81.5 per cent) publish overwhelmingly through cross-border teams, whereas Indonesia (38.9 per cent), Vietnam (30.0 per cent), Thailand (33.3 per cent) and Turkey (33.3 per cent) publish predominantly through domestic teams. For Indonesian scholarship in particular, this represents a visible and addressable structural gap: the country ranks fifth in output but well below the Scopus mean in international co-authorship.

Table 5. Twelve most represented countries and international collaboration.

Ra	Country	Articl	% of Sc	Articles with internat co-authorship	% Internationall authored
1	China	62	30.0	34	54.8
2	Saudi Arabia	27	13.0	22	81.5
3	United Kingdo	24	11.6	22	91.7
4	Malaysia	20	9.7	16	80.0
5	Indonesia	18	8.7	7	38.9
6	India	15	7.2	13	86.7
7	France	13	6.3	13	100.0

Ra	Country	Articl	% of Sco	Articles with internat co-authorship	% Internationally authored
8	Thailand	12	5.8	4	33.3
9	Turkey	12	5.8	4	33.3
10	United States	11	5.3	11	100.0
11	Italy	11	5.3	9	81.8
12	Viet Nam	10	4.8	3	30.0
	Scopus total	**207**	**100.0**	**97**	**46.9**

Source: Authors' own work. Percentages of Scopus sum to more than 100 because articles with authors from several countries are counted once per country.

Three-field analysis of references, authors and keywords

Figure 3 presents a three-field plot connecting cited references (left), authors (centre) and merged keywords (right), which traces how the field's intellectual inheritance is channelled through its most active researchers into its thematic output. The left-hand column is dominated not by substantive theory but by methodological references: Podsakoff et al. (2003) on common method bias, cited by 53 articles; Fornell & Larcker (1981) on convergent and discriminant validity, cited by 50; Henseler et al. (2015) on the heterotrait–monotrait criterion, cited by 46; and Hair et al. (2019) on reporting PLS-SEM results, cited by 37. The substantive anchors follow: Teece (2007) with 35 citing articles, Teece et al. (1997) with 57 across indexed variants, Mikalef & Gupta (2021) with 26 and Barney (1991) with 26.

This ordering is diagnostic. A field whose most-shared references are instruments for validating survey measurement, rather than theories about the phenomenon under study, is one whose collective identity is methodological before it is theoretical. It explains both the field's rapid growth, since a standardised measurement apparatus lowers the cost of entry, and its fragmentation, since shared instruments do not impose a shared model. The right-hand column shows the thematic destinations of these inheritances, with digital transformation, artificial intelligence and supply chain resilience receiving the densest flows, while decision making, green innovation, circular economy and industry 4.0 form a secondary tier.

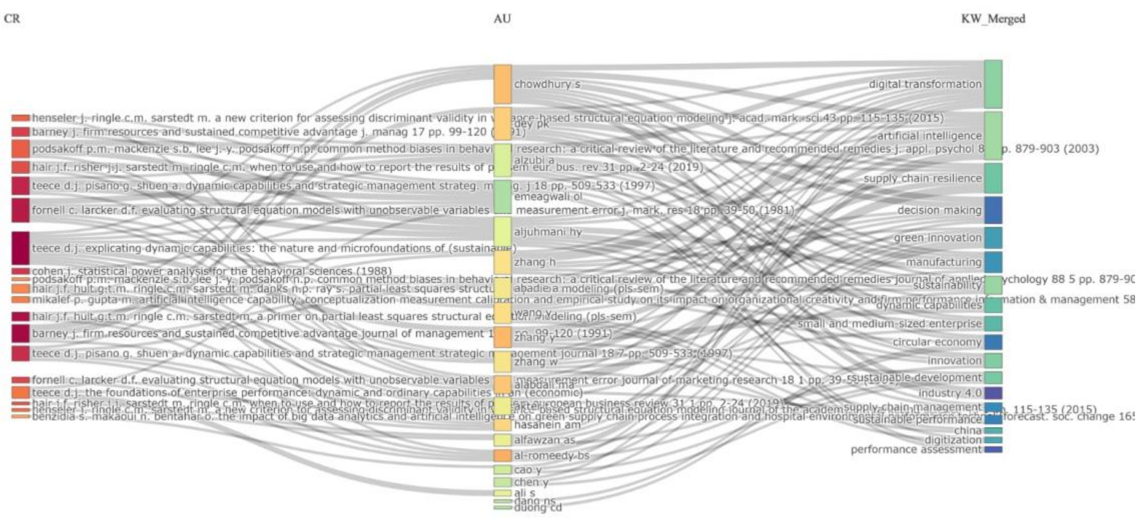

Figure 3. Three-field plot linking cited references, authors and merged keywords.

Source: Authors' own work, generated with Biblioshiny.

Keyword frequency: word cloud and tree map

Figures 4 and 5 display the merged author and index keywords as a word cloud and a tree map respectively. The two visualisations report the same underlying distribution, in which artificial intelligence occurs 51 times (9 per cent of keyword occurrences), sustainability 40 times (7 per cent), digital transformation 36 times (6 per cent), innovation 33 times (6 per cent), sustainable development 25 times (4 per cent), supply chain resilience 22 times (4 per cent), dynamic capabilities 17 times (3 per cent) and small and medium-sized enterprise 15 times (3 per cent). Restricting attention to author-supplied keywords, which reflect how researchers position their own contributions rather than how indexers classify them, produces a slightly different ranking led by digital transformation (32), artificial intelligence (31), supply chain resilience (22), sustainability (17) and dynamic capabilities (17).

Figure 4. Word cloud of merged author and index keywords.

Source: Authors' own work, generated with Biblioshiny.

The tree map in Figure 5 adds proportional information that the word cloud obscures. Its area-encoded blocks make visible how steeply the distribution falls away after the leading terms, and where the model's constructs sit within that decline. Dynamic capabilities occupie’s 3 per cent of keyword occurrences and organisational resilience 2 per cent, while the vocabulary of inclusivity does not appear among the fifty most frequent keywords at all. The tree map also reveals the field's contextual specialisations: China (14 occurrences) and Saudi Arabia (7) appear as keywords in their own right, indicating that a meaningful share of the Scopus positions itself as country-specific evidence, while pls-sem (9) and panel data (6) appear as keywords, confirming that method is treated as a positioning device.

Figure 5. Tree map of the most frequent merged keywords.

Source: Authors' own work, generated with Biblioshiny.

Word dynamics: the cumulative growth of key terms

Figure 6 traces the cumulative occurrence of the ten most frequent terms across the review window and reveals the sequence in which the field's vocabulary was assembled. Digital transformation and sustainability are the only terms with any presence in 2022; artificial intelligence overtakes both during 2024 and separates decisively thereafter, reaching 51 cumulative occurrences by 2026 against 40 for sustainability and 36 for digital transformation. Dynamic capabilities and small and medium-sized enterprise register no occurrences until 2024 and then rise steeply, while supply chain resilience appears only from 2024 and reaches 22 by 2026.

Read against the construct coding, this sequence has a specific meaning. The theoretical vocabulary of dynamic capabilities entered the field after the technological vocabulary of AI and digital transformation, not before it. The literature has been theorising a phenomenon retrospectively, importing an established capability framework to explain an already-observed technological shift. This accounts for a recurring structural feature of the Scopus, in which dynamic capability is frequently positioned as a mediator or moderator of technology effects rather than as the antecedent that the dynamic capabilities view itself specifies. The model advanced in Section 5 restores the theoretically prior ordering.

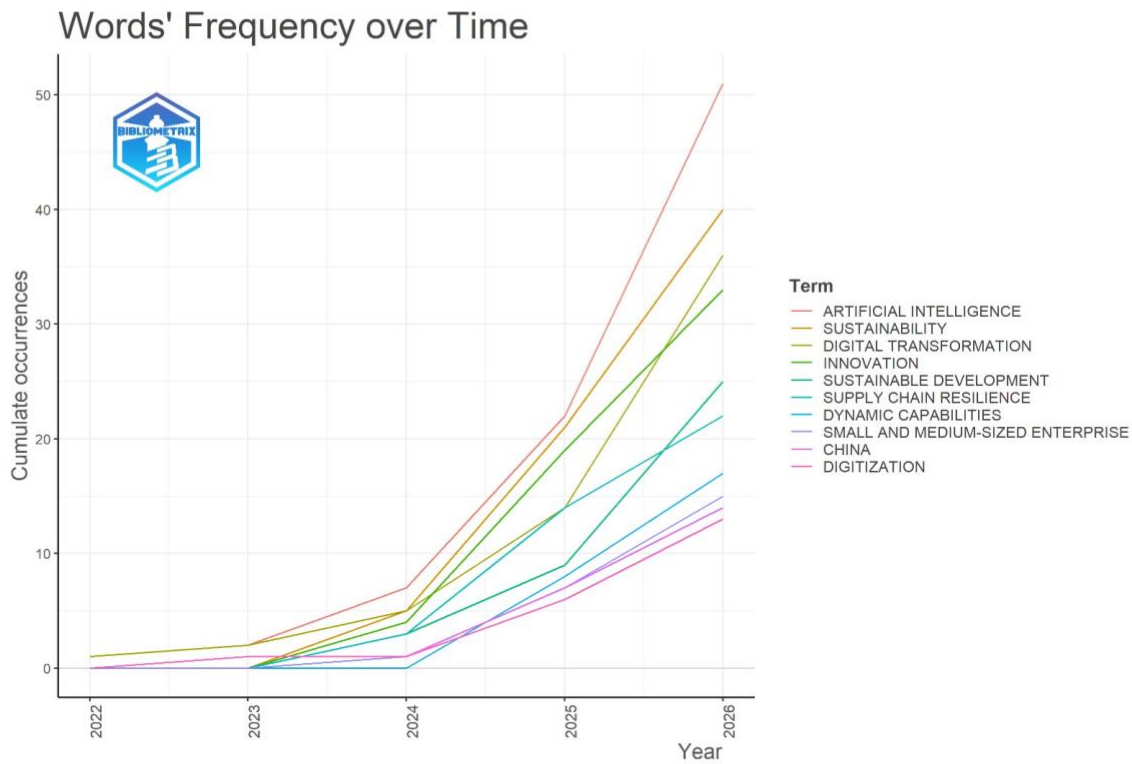

Figure 6. Cumulative occurrence of the ten most frequent terms, 2022–2026.

Source: Authors' own work, generated with Biblioshiny.

Trend topics

Figure 7 plots trend topics by the year of median occurrence, with point size proportional to term frequency. The analysis divides the Scopus cleanly into two temporal groups. Sustainability, innovation and supply chain resilience have early median years, indicating terms established at the outset of the window and used consistently since. Artificial intelligence, digital transformation and sustainable development have late median years, indicating terms whose usage is concentrated in the most recent publications and still accelerating.

The position of supply chain resilience deserves particular note. It is among the earliest-established terms yet, on the evidence of Table 4, it anchors the Scopus's most-cited work. This combination of early establishment and continuing citation weight identifies supply chain resilience as the field's consolidated core, the relationship on which sufficient cumulative evidence exists to support model building. Artificial intelligence and digital transformation, by contrast, are still in an expansionary phase where terminological volatility remains high and measurement conventions are unsettled.

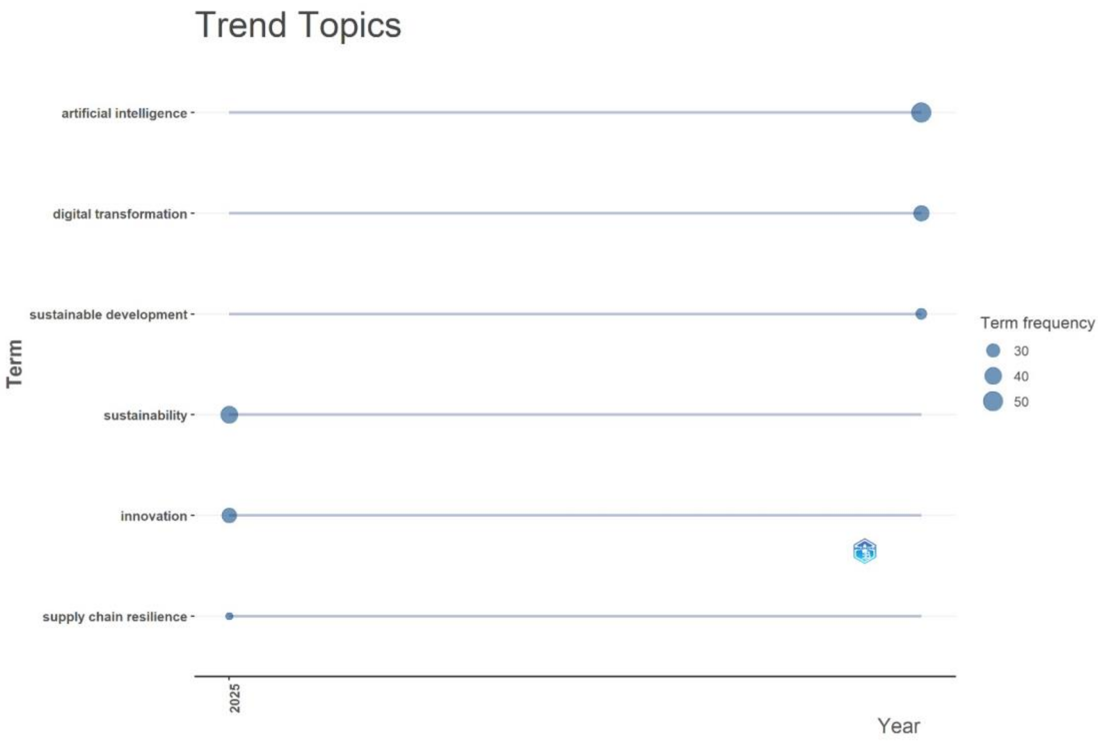

Figure 7. Trend topics by median year of occurrence.

Source: Authors' own work, generated with Biblioshiny.

Conceptual structure: keyword co-occurrence and thematic mapping

Figure 8 presents the keyword co-occurrence network generated in Biblioshiny, in which node size is proportional to occurrence frequency, edge thickness to co-occurrence strength, and colour to cluster membership as determined by the Louvain algorithm. Five clusters are resolved, summarised in Table 6.

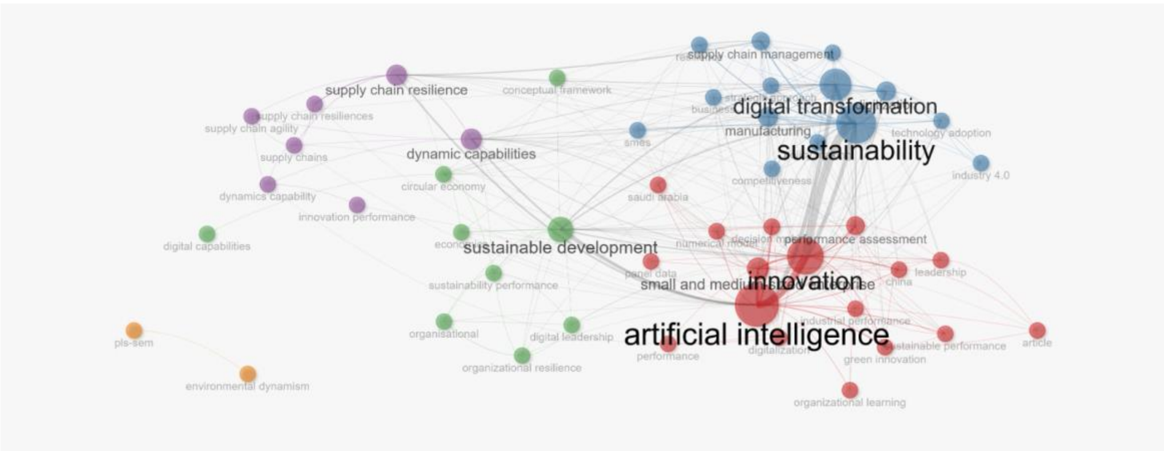

Figure 8. Keyword co-occurrence network.

Source: Authors' own work, generated with Biblioshiny.

Table 6. Keyword clusters identified in the co-occurrence network.

Cluster	Label	Core keywords	Interpretation
1 (blue)	Digital transformation and sustainability	digital transformation, sustainability, supply chain management, manufacturing,	The technological-managerial core: how firms adopt digital technologies and

Cluster	Label	Core keywords	Interpretation
		technology adoption, industry 4.0, competitiveness, SMEs, strategic approach	account for the sustainability consequences
2 (red)	Artificial intelligence and innovation performance	artificial intelligence, innovation, small and medium-sized enterprise, performance assessment, decision making, digitalization, green innovation, leadership, industrial performance, sustainable performance, organizational learning, China, Saudi Arabia	The performance-outcome cluster, linking AI to innovation and firm results, with strong country-specific anchoring
3 (purple)	Supply chain resilience and dynamic capabilities	supply chain resilience, dynamic capabilities, supply chains, supply chain agility, dynamics capability, digital capabilities, innovation performance	The capability-resilience cluster, theoretically the closest to the review model and the Scopus's most-cited segment
4 (green)	Sustainable development and the circular economy	sustainable development, circular economy, economics, sustainability performance, digital leadership, organizational resilience, conceptual framework, organisational	The normative-environmental cluster, oriented to development goals and circularity rather than firm-level performance
5 (orange)	Methodologica l	pls-sem, environmental dynamism	A small, peripheral cluster confirming that method and boundary conditions form a recognisable sub-conversation

Source: Authors' own work, based on Biblioshiny co-occurrence analysis.

The structural relationship among these clusters is as informative as their content. Clusters 1 and 2 occupy the network's dense centre and are heavily interlinked; cluster 3, which contains the constructs closest to the review model, sits at the network's upper-left periphery and connects to the centre principally through sustainable development; and cluster 5 is almost detached. The capability-resilience conversation, in other words, is not yet integrated with the AI-performance conversation, even though the two share both a theoretical vocabulary and, as Table 4 shows, several of the same highly cited authors.

Figure 9 presents the strategic thematic map, positioning clusters by centrality and density. Artificial intelligence, digital transformation and small and medium-sized enterprise occupy the motor-themes quadrant: they are both well developed internally and strongly connected to the rest of the field, and they drive its current agenda. Sustainability, innovation and dynamic capabilities occupy the basic-themes quadrant, indicating high relevance but comparatively low internal development, which is characteristic of transversal constructs used across many sub-conversations without a settled specification of their own. Sustainable development, green innovation and organisational resilience sit near the boundary of the niche quadrant, developed but insufficiently connected. Supply chain resilience, performance and pls-sem fall just below the density threshold at moderate centrality. Leadership, competitiveness and article form an isolated niche, while sustainable performance, industrial performance and organizational learning fall in the emerging-or-declining quadrant.

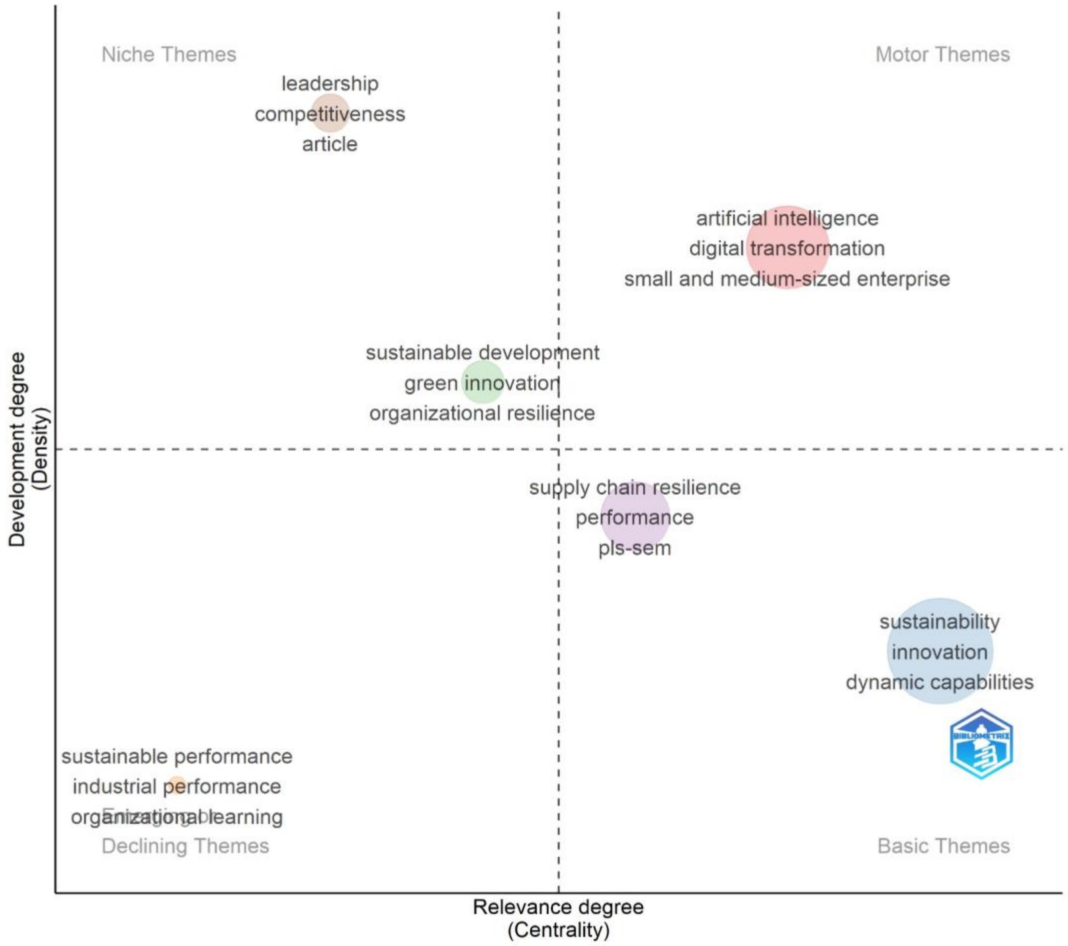

Figure 9. Strategic thematic map of the Scopus.

Source: Authors' own work, generated with Biblioshiny.

The most consequential observation from Figure 9 concerns sustainable performance. In a literature whose declared purpose is to explain how technological capability produces sustainable outcomes, the outcome construct itself sits in the low-centrality, low-density quadrant. Given the Scopus's growth trajectory, it is better read as emerging than as declining, but its position confirms that the field currently attends far more closely to its antecedents than to its dependent variable. Read together, Figures 8 and 9 describe a literature with a strong technological engine, a well-developed resilience mechanism that remains peripherally connected, and an under-developed outcome, which is precisely the configuration the integrative model in Section 5 is designed to address.

VOSviewer network and density visualisation

Figures 10 and 11 present the VOSviewer keyword co-occurrence network and its item density visualisation. Applying a different normalisation procedure and a lower occurrence threshold than Biblioshiny, VOSviewer resolves a finer-grained structure of approximately ten clusters, which corroborates the five-cluster solution while adding detail. Digital transformation forms the network's largest node and its structural hub; supply chain resilience, dynamic capabilities, circular economy, sustainability, green innovation, SMEs and industry 4.0 form the surrounding ring of major nodes. The finer resolution exposes specialised sub-conversations invisible at the coarser scale, including a decision-oriented cluster around AI-driven decision-making, big data analytics, change management and digital transformational leadership; an ESG-and-circularity cluster; a governance cluster linking adaptive policy design to digital performance; and a methodological periphery around PLS-SEM.

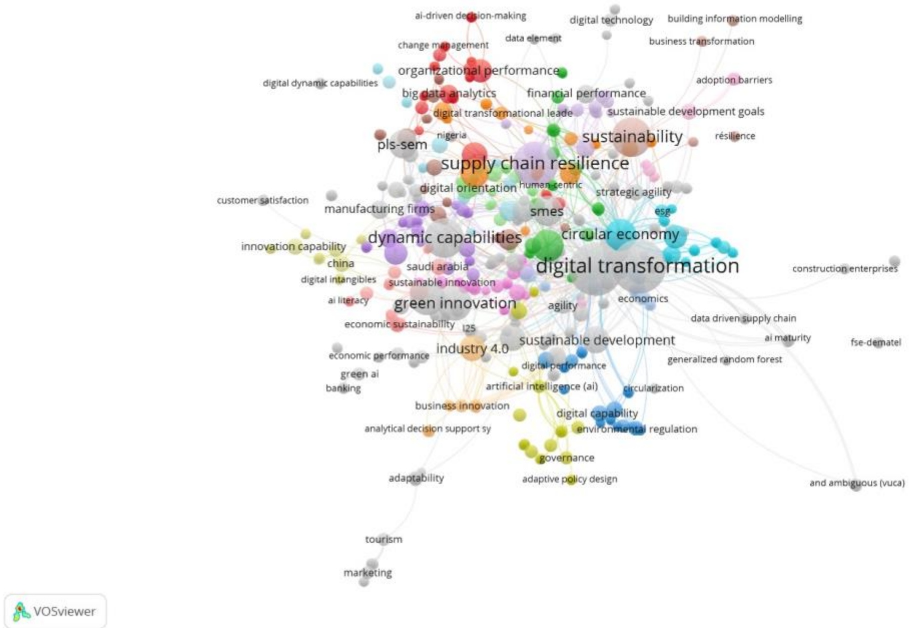

Figure 10. VOSviewer keyword co-occurrence network visualisation.

Source: Authors' own work, generated with VOSviewer 1.6.20.

The density visualisation in Figure 11 converts this structure into a map of research intensity, in which brightness indicates the concentration of items and their weights. A single high-intensity zone surrounds digital transformation and extends to supply chain resilience, circular economy, SMEs and sustainability. Green innovation, dynamic capabilities and industry 4.0 form a moderately dense band at the margin of this zone. The analytical value of the density map lies in what it renders dark. Terms such as AI literacy, green AI, adoption barriers, adaptive policy design, digital dynamic capabilities, human-centric approaches and AI maturity appear in low-intensity regions, indicating that they are present in the literature but not yet connected to its dense core. These are candidate sites for contribution: sufficiently established to be recognisable to reviewers, sufficiently unsaturated to permit original work. The proposed model's inclusivity construct belongs to precisely this category.

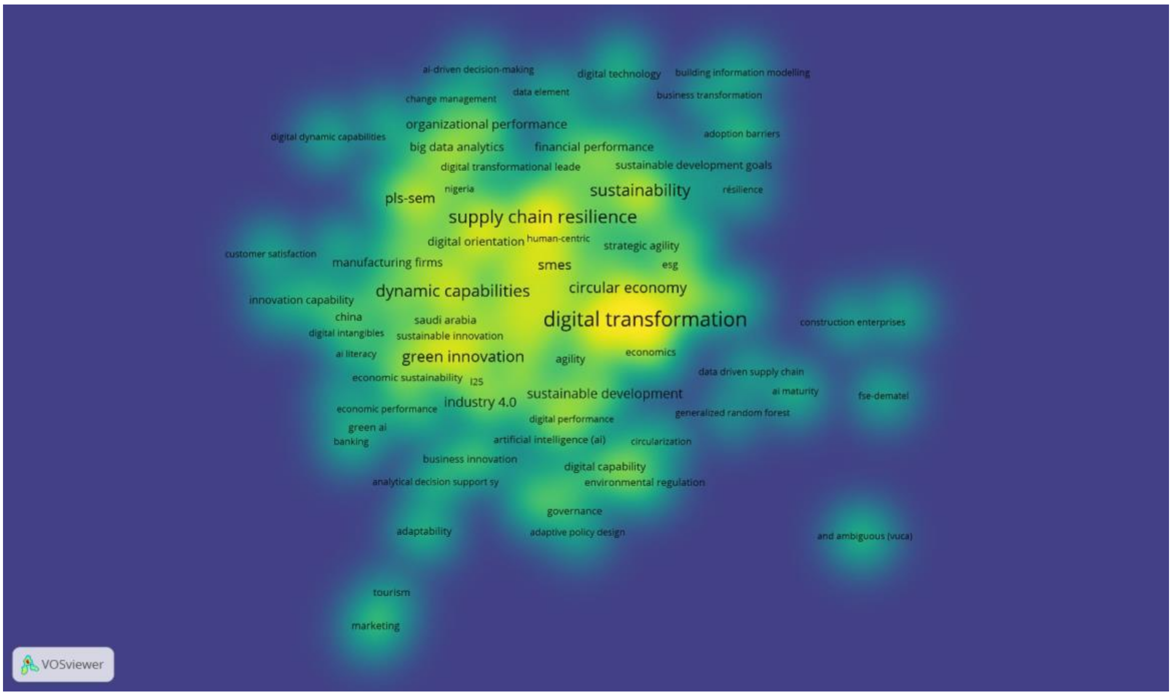

Figure 11. VOSviewer item density visualisation.

Source: Authors' own work, generated with VOSviewer 1.6.20.

Construct coverage and the evidence gap

Bibliometric mapping identifies which terms a literature uses. It cannot establish which relationships that literature has actually tested. The construct coding described in Section 3.5 was designed to close this gap, and its results are reported in Figure 12 and Table 7.

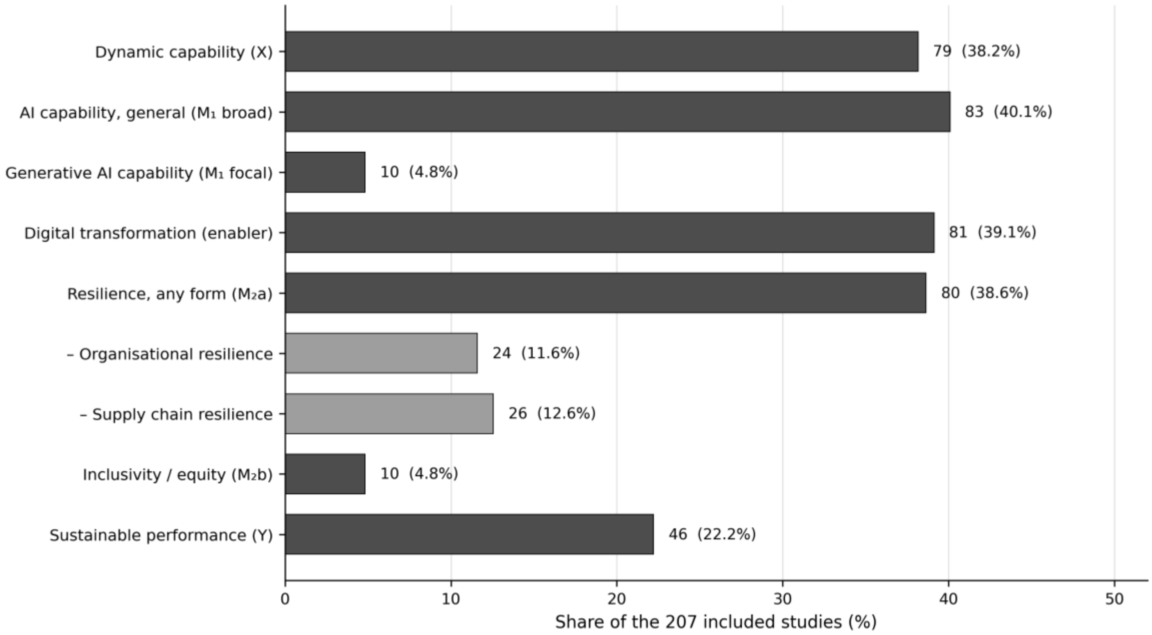

Figure 12. Coverage of the review-model constructs across the 207 included studies.

Source: Authors' own work, based on construct-level coding of the included Scopus.

Table 7. Construct coverage across the 207 included studies.

Model position	Construct	Studies (n)	% of Scopus	Assessment
X	Dynamic capability (sensing, seizing, reconfiguring, absorptive capacity)	79	38.2	Well covered
Enabler	Digital transformation / digitalisation	81	39.1	Well covered
M_1 (broad)	AI capability, general	83	40.1	Well covered
M_1 (focal)	Generative AI capability	10	4.8	Severely under-covered
M_2a	Resilience, any form	80	38.6	Well covered
M_2a (i)	Organisational resilience	24	11.6	Moderately covered
M_2a (ii)	Supply chain resilience	26	12.6	Moderately covered
M_2b	Inclusivity, inclusion, equity, digital divide	10	4.8	Severely under-covered
Y	Sustainable performance	46	22.2	Moderately covered
Y (related)	Green innovation	28	13.5	Moderately covered
Y (related)	Circular economy	15	7.2	Under-covered
Context	SMEs	50	24.2	Moderately covered
Context	Industry 4.0 / 5.0	16	7.7	Under-covered

Source: Authors' own work. Categories are not mutually exclusive; a study may address several constructs.

The distribution is sharply bimodal. Four constructs — dynamic capability, digital transformation, general AI capability and resilience — appear in roughly two-fifths of the Scopus each. Two constructs central to the proposed model appear in fewer than one study in twenty: generative AI capability (10 studies, 4.8 per cent) and inclusivity (10 studies, 4.8 per cent). The generative AI finding is striking in a Scopus whose growth was itself triggered by generative AI: the field has expanded in response to a technology it has largely continued to measure with pre-generative instruments, exactly the operationalisation lag that Feuerriegel et al. (2024) anticipate. The inclusivity finding is more serious still, because it is not a lag but an omission. A literature that names sustainability in 40 keyword occurrences and sustainable development in 25 addresses the social dimension of the triple bottom line in one study in twenty.

Figure 13 examines joint coverage, which is the decisive test. Of 207 studies, five (2.4 per cent) model dynamic capability, AI capability, resilience and sustainable performance together. Only one (0.5 per cent) does so with generative AI specified as the technology construct. Not a single study incorporates inclusivity into that chain, and inclusivity co-occurs with sustainable performance in one study only. Pairwise co-occurrence confirms that the field's integration is partial rather than absent: dynamic capability co-occurs with resilience in 34 studies and with AI capability in 31; AI capability co-occurs with resilience in 32; and under the broader reading in which any reference to sustainability is counted, dynamic capability co-occurs with sustainability in 55 studies, AI capability in 52 and resilience in 52. The field, in short, has assembled every adjacent pair of the causal chain while assembling the chain itself almost never.

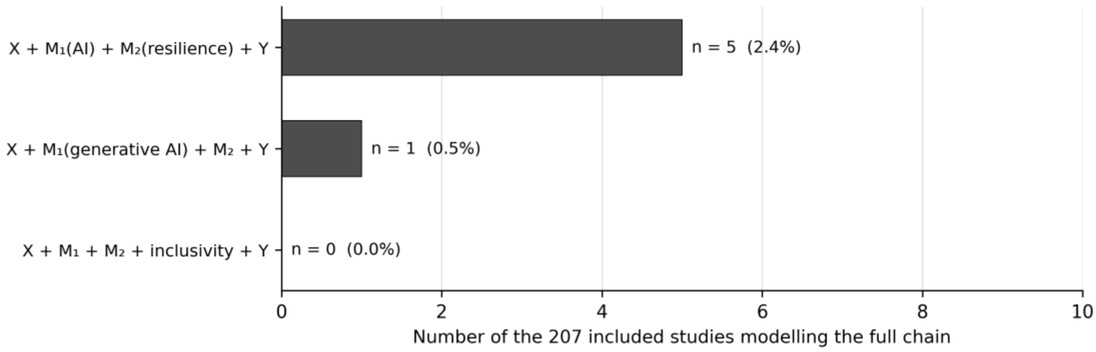

Figure 13. Joint coverage of the full causal chain across the 207 included studies.

Source: Authors' own work, based on construct-level coding.

Methodological characteristics of the evidence base

Table 8 reports the distribution of study designs. Survey-based quantitative research using structural equation modelling accounts for 137 studies (66.2 per cent), with partial least squares estimation identifiable in 70 studies (33.8 per cent) and fuzzy-set qualitative comparative analysis in 11 (5.3 per cent), the latter exemplified by Zhang et al. (2023), who combine PLS-SEM with fsQCA to identify configurations of factors driving digital transformation in construction enterprises. Conceptual and other work accounts for 22 studies, reviews and bibliometric analyses for 14, multi-criteria and configurational studies for 13, archival and econometric studies for 12, qualitative and case-based research for 5 (2.4 per cent) and computational or simulation work for 4.

Table 8. Distribution of study designs in the Scopus.

Study design	Studies (n)	% of Scopus
Survey-based quantitative (SEM / PLS-SEM)	137	66.2
Conceptual and other	22	10.6
Review and bibliometric	14	6.8
Multi-criteria decision-making and configurational	13	6.3
Archival and econometric	12	5.8
Qualitative and case study	5	2.4
Computational and simulation	4	1.9
Total	207	100.0

Source: Authors' own work, based on priority-rule coding of the included Scopus.

This concentration has three consequences for how the review's other findings should be read. First, the evidence base is overwhelmingly cross-sectional and perceptual: constructs are measured through managerial self-report at a single point in time, so the causal ordering implied throughout the Scopus rests on theoretical argument rather than temporal identification. The prominence of Podsakoff et al. (2003) among the field's most-cited references indicates that researchers are aware of the resulting common-method risk, but statistical remedies cannot substitute for design. Second, the scarcity of qualitative research (2.4 per cent) leaves the field with little process evidence on how capabilities are actually built, and this is likely to be one reason generative AI capability remains poorly specified: a construct whose organisational form is still emerging is better approached inductively before it is instrumented. Third, the near-absence of longitudinal and quasi-experimental designs means that the sustainability outcome, which by definition unfolds over time, is almost always measured contemporaneously with its supposed causes.

These characteristics do not invalidate the Scopus. Its rapid convergence on a shared measurement apparatus is what has allowed a coherent field to form in four years. But they do define the standard against which new primary research should be judged, and they identify longitudinal design, objective performance measurement and inductive specification of generative AI capability as the methodological contributions most likely to advance the field.

Toward an Integrative Model of Sustainable Performance

The results support a specific diagnosis. The field has a strong technological engine, a well-evidenced resilience mechanism, an under-developed outcome construct, an outdated technology specification and a missing social mediator. The model presented in Figure 14 addresses these five conditions simultaneously by restoring the theoretically prior ordering of constructs and by specifying the two mediating states through which capability is converted into performance.

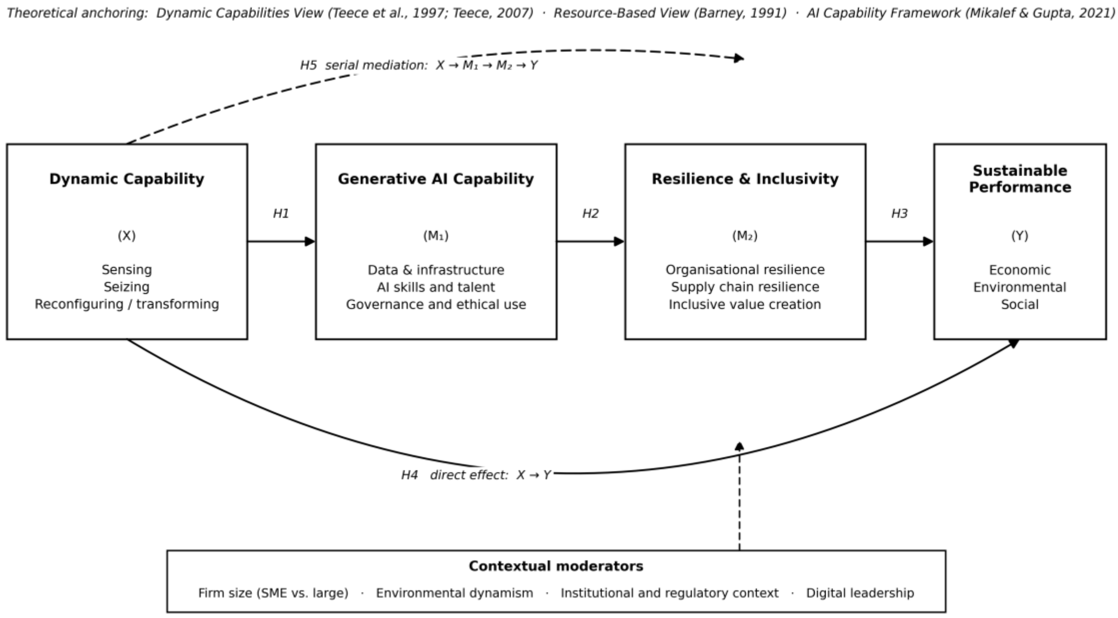

Figure 14. Integrative model of dynamic capability, generative AI capability, resilience and inclusivity, and sustainable performance.

Source: Authors' own work.

Dynamic capability enters the model as the exogenous construct, specified through Teece (2007) microfoundations of sensing, seizing and reconfiguring. This placement is a correction as well as a specification. As Section 4.6 established, the capability vocabulary entered this literature after the technology vocabulary and has frequently been positioned as a consequence or contingency of technology adoption. Theory requires the opposite ordering: it is the firm's prior capacity to sense opportunity, commit resources and reconfigure its asset base that determines whether a generative AI opportunity is recognised, funded and absorbed. Warner & Wäger (2019) demonstrate this sequence directly, and the model adopts it.

Generative AI capability enters as the first mediator, specified through three dimensions drawn from Mikalef & Gupta (2021) and adapted to the generative paradigm following Feuerriegel et al. (2024): data and infrastructure readiness, AI skills and talent, and governance and ethical use. The third dimension is not an ethical addendum but a constitutive element of the construct. Where predictive AI capability could treat governance as a compliance overlay, generative systems that hallucinate, obscure provenance and are directly accessible to non-specialist employees make governance a determinant of whether capability produces value or liability.

Resilience and inclusivity enter jointly as the second mediator, representing the organisational states through which technological capability is converted into durable performance. Resilience governs the economic and operational conversion and is the best-evidenced relationship in the Scopus (Belhadi et al. (2024); Dey et al. (2024); Yu et al. (2024)). Inclusivity governs the social and legitimacy conversion and is, on this review's evidence, untested. Their joint specification is deliberate: modelling them separately would reproduce the fragmentation the review identifies, whereas modelling them together permits the trade-off between operational efficiency and social participation to be estimated rather than assumed. Sustainable performance is the endogenous construct, specified across economic, environmental and social dimensions (Elkington, 1997), with the social dimension measured rather than asserted.

The model yields five testable propositions, stated below and corresponding to the paths labelled in Figure 14.

P1. Dynamic capability is positively associated with generative AI capability. Firms with stronger sensing, seizing and reconfiguring routines recognise generative AI opportunities earlier, commit resources to them more decisively, and reconfigure roles and processes more effectively than firms with comparable resource endowments but weaker routines.

P2. Generative AI capability is positively associated with organisational and supply chain resilience and with inclusive value creation. The resilience component extends the established AI–resilience relationship to the generative paradigm; the inclusivity component is conditional on the governance dimension, such that generative AI capability enhances inclusivity where governance and ethical use are strong and may reduce it where they are weak.

P3. Resilience and inclusivity are positively associated with sustainable performance, with resilience operating primarily on the economic and environmental dimensions and inclusivity primarily on the social dimension.

P4. Dynamic capability retains a positive direct association with sustainable performance after accounting for both mediators, reflecting capability effects that operate through channels other than AI.

P5. The indirect effect of dynamic capability on sustainable performance through the serial path of generative AI capability and the resilience–inclusivity complex is positive and exceeds the direct effect, such that the relationship is substantially rather than partially mediated.

Four contextual moderators are specified. Firm size is expected to condition the first path, since SMEs face capability-accumulation constraints that large firms do not, although Dey et al. (2024) show the mechanism operates in SMEs nonetheless. Environmental dynamism is expected to strengthen the capability paths, consistent with Eisenhardt & Martin (2000) argument that dynamic capabilities matter most where markets shift fastest. Institutional and regulatory context is expected to condition the inclusivity path, given the Scopus's concentration in economies with divergent regulatory regimes. Digital leadership is expected to condition the governance dimension of generative AI capability, following Asbeetah et al. (2025).

Conclusion

This study set out to map the research field connecting dynamic capability, artificial intelligence capability, resilience, inclusivity and sustainable performance, and to derive from that map an integrative and testable model. Applying a PRISMA 2020 review protocol and dual-software bibliometric analysis to 207 Scopus-indexed articles published between 2022 and 2026, it finds a field expanding at close to exponential rates, with output rising from one article in 2022 to 117 in 2026, distributed across 90 sources and 686 authors, and produced through international collaboration in 46.9 per cent of cases.

The field's conceptual structure resolves into five clusters spanning digital transformation and sustainability, artificial intelligence and innovation performance, supply chain resilience and dynamic capabilities, sustainable development and the circular economy, and a methodological periphery. Thematic mapping identifies artificial intelligence, digital transformation and SMEs as the motor themes driving the current agenda, and sustainability, innovation and dynamic capabilities as basic themes of high relevance but limited internal development.

The review's principal contribution, however, lies in what construct-level coding reveals beneath this apparently healthy structure. Dynamic capability and resilience each appear in roughly two-fifths of the Scopus, but generative AI capability appears in 4.8 per cent and inclusivity in 4.8 per cent. Five studies model the dynamic-capability-to-sustainable-performance chain, one does so with generative AI, and none incorporates inclusivity. A field that grew in response to generative AI has largely continued to measure a previous technological paradigm, and a field organised around sustainability has left the social dimension of the triple bottom line substantially unmeasured.

The integrative model proposed in response specifies dynamic capability as the antecedent, generative AI capability as the first mediator with governance as a constitutive dimension, resilience and inclusivity jointly as the second mediator, and sustainable performance measured across all three dimensions as the outcome, moderated by firm size, environmental dynamism, institutional context and digital leadership. Its five propositions are stated so as to be falsifiable, and the measurement conventions already dominant in the Scopus make them immediately testable.

Implications

Theoretical implications

The review makes four theoretical contributions. First, it demonstrates empirically, rather than asserting rhetorically, that the field's causal chain is unassembled: five studies of 207 model it in part, one with generative AI, none with inclusivity. Claims of fragmentation are common in review articles; measuring fragmentation at construct level is less so, and the coding procedure introduced in Section 3.5 is transferable to other literatures where co-word analysis alone would overstate integration.

Second, it restores the theoretically warranted ordering of dynamic capability and technology capability. The word-dynamics analysis shows that the capability vocabulary was imported after the technology vocabulary, with the consequence that dynamic capability is frequently modelled as a consequence or contingency of adoption. Specifying it as the antecedent returns the literature to the logic of Teece et al. (1997) and generates different and testable predictions about the sequence of capability building.

Third, it specifies generative AI capability as a construct distinct from AI capability generally, with governance and ethical use as a constitutive rather than peripheral dimension. Given that only ten studies in the Scopus address generative AI at all, this specification is a necessary precondition for the field to measure the technology that triggered its growth.

Fourth, and most substantively, it repositions inclusivity from rhetorical commitment to modelled mediator. The finding that inclusivity appears in 4.8 per cent of a sustainability-oriented Scopus, and in none of the studies modelling the full chain, identifies a gap that is structural rather than incidental. Treating inclusivity as a mediator alongside resilience, drawing on the inclusive-innovation tradition (George et al. (2012); Prahalad & Hart (2002)), gives the social dimension of the triple bottom line the same analytical status the environmental dimension already enjoys.

Practical implications

For managers, the model implies a sequence rather than a portfolio. The most consistent message of the evidence is that firms with weak sensing and reconfiguring routines do not obtain returns from AI investment commensurate with those obtained by firms with strong ones, because the capability determines whether the technology is directed at the right problem and absorbed into working practice. Generative AI investment should therefore follow, not substitute for, investment in the organisational routines that identify opportunity and reallocate resources.

The governance dimension carries a related practical implication. Because generative systems are accessible to employees without technical training, capability accumulates in a decentralised and often unmanaged way. Firms that establish provenance standards, usage policies and review procedures early are building capability, not constraining it. The resilience evidence, meanwhile, gives managers an intermediate objective that is measurable well before sustainability outcomes materialise: if AI investment is not improving the ability to anticipate, absorb and recover from disruption, the pathway to sustainable performance is unlikely to be operating. For SMEs specifically, Dey et al. (2024) and S. A. R. Khan et al. (2025) provide evidence that the mechanism functions under resource constraint, which argues for targeted capability building rather than deferred adoption.

Policy implications

For policymakers, three implications follow. The geographic distribution in Table 5 shows that research on this question is concentrated in rapidly digitalising economies, several of which combine high research output with low international collaboration. For Indonesia, which ranks fifth in output but publishes only 38.9 per cent of its work through international teams against a Scopus mean of 46.9 per cent, collaboration funding is a direct and low-cost lever on research quality and visibility.

The inclusivity finding has a sharper policy edge. Where research does not measure the distributional consequences of AI adoption, policy cannot be evidence-based about them. Public funding that requires inclusivity outcomes to be measured, and public procurement that requires them to be reported, would change the incentives that produce the 4.8 per cent coverage documented here. Finally, the governance dimension of generative AI capability suggests that regulation and capability building are complements rather than substitutes: clear standards on provenance, disclosure and permissible use reduce the uncertainty that deters adoption among smaller firms, and are therefore an enabling instrument as well as a protective one.

Limitations and Recommendations for Further Research

Four limitations qualify these conclusions. First, the review draws on a single database. Scopus offers the broadest coverage of the relevant journals and the metadata structure both analytical packages require, but Web of Science indexes titles Scopus does not, and a dual-database design with de-duplication would raise coverage at the cost of additional reconciliation. Second, the restriction to English-language, final-stage journal articles excludes conference proceedings, book chapters, non-English scholarship and grey literature. In a field this recent, conference papers may carry a disproportionate share of the newest work, and the exclusion of Chinese- and Indonesian-language research is a particular limitation given the prominence of both countries in Table 5.

Third, the 2022–2026 window is justified by the review's focus on the generative AI era but necessarily truncates the intellectual history of constructs, such as dynamic capability and resilience, that were developed decades earlier. Co-citation analysis partially compensates by recovering the foundational works the Scopus cites, but a longer window would permit the evolution of these constructs to be traced directly. Fourth, construct coding was performed on titles, abstracts and keywords rather than full texts. This procedure reliably identifies constructs that studies foreground and may under-count those examined only in a study's body; the coverage figures in Table 7 should therefore be read as measures of prominence rather than exhaustive presence, although this qualification does not affect the joint-coverage finding, since a study modelling the full chain would foreground it.

Five research directions follow directly. The first is empirical testing of the model in Figure 14, ideally through a multi-country design spanning contexts with divergent regulatory regimes, which the Scopus's geographic distribution makes both feasible and analytically valuable. The second is the development and validation of a generative AI capability instrument, since existing scales were developed for predictive AI and the governance dimension is not adequately represented in any of them; given how recently the construct emerged, an inductive qualitative phase should precede scale development.

The third is the construction of an inclusivity measure appropriate to the firm level, capturing workforce transition and reskilling, supplier diversity and the integration of smaller partners into digital networks, and access for underserved customers. Without such an instrument the social dimension of sustainable performance will remain rhetorical. The fourth is methodological: the Scopus's 66.2 per cent concentration in cross-sectional survey designs and its 2.4 per cent share of qualitative work identify longitudinal designs, objective performance measures and process research as the contributions most likely to advance the field. The fifth is contextual, and concerns SMEs in emerging economies. They appear in 24.2 per cent of the Scopus and face the sharpest form of the capability constraint the model describes, yet the evidence on how they build generative AI capability under resource limitation remains thin.

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