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Generative AI adoption culture in organizations: A bibliometric review and research agenda (2022–2026)

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A B S T R A C T

Generative artificial intelligence (GenAI) has reshaped organizational work since the release of ChatGPT in late 2022, yet research on the cultural dimensions of its adoption remains fragmented. This study synthesizes the emerging field through a bibliometric review combining performance analysis, science mapping, and the Theory–Context–Characteristics–Methodology (TCCM) framework. A Scopus search executed on 5 May 2026 yielded 257 records, refined to 128 by automatic filters, and reduced to 69 articles after PRISMA 2020 screening. Analysis employed bibliometrix (R 4.3.0) and four VOSviewer 1.6.20 networks. The field exhibits an annual growth rate of 114.07%, with publications rising from one in 2022 to 36 in 2025 and 21 in early 2026 across 65 sources and 23 countries (China leads with 12 articles), anchored by Ng et al. (2025), Jo and Bang (2023), and Lee and Park (2024). The keyword map yields four thematic clusters; the co-citation map reveals three intellectual sub-structures (Technology Acceptance, Methodological and Applied GenAI, and GenAI in Management). Both layers converge on a technology-acceptance dominant, methodologically homogeneous, and culturally thin configuration: classical culture references (Schein, Cameron, and Quinn) and dedicated AI-ethics works do not reach the co-citation core. To redress this asymmetry, we propose an integrative framework: Leadership Vision → AI Literacy and Trust → Psychological Safety → Ethical Climate → GenAI Adoption Culture → Productivity, Innovation, and Well-being. The agenda outlines five priorities, including cross-cultural instruments, longitudinal multi-wave designs, and emerging-market studies foregrounding Indonesia and ASEAN.

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1. Introduction

Since OpenAI released ChatGPT on 30 November 2022, knowledge workers worldwide have delegated first drafts, brainstorms, and routine analyses to a generative system that speaks their own language. Within two years, large language models (LLMs) such as GPT-4, Gemini, Claude, and Copilot have become part of everyday workflows, from drafting executive memos to scaffolding strategic decisions (Callari & Puppione, 2025; Kelm & Johann, 2025). Recent scholarship documents a rapid wave of organizational GenAI piloting across sectors and geographies, with adoption deepening through 2025–2026 in multinational corporations and educational institutions alike (Ng et al., 2025; Rajaram & Tinguely, 2024).

Behind these headline diffusion numbers lies a quieter story. Practitioners describe an implementation gap: organizations procure infrastructure, sign enterprise licenses, and announce pilots, only to watch employees disengage, distrust AI outputs, or quietly route around tools they were expected to embrace (Jo & Bang, 2023a; Rajaram & Tinguely, 2024; Zhao et al., 2024). The gap is rarely technical; more often than not, it is cultural.

This pattern positions organizational culture as a critical mediator of GenAI adoption outcomes. Schein (2010) defines organizational culture as the pattern of basic assumptions, espoused values, and shared norms that shape members' behavior. Although the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT)

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have long informed studies of individual adoption, the field has produced only fragmented evidence on the cultural configurations that distinguish successful from unsuccessful GenAI integration (Chu, 2023). The field is also expanding rapidly: a preliminary Scopus search on 5 May 2026 located 257 records linking GenAI and organizational culture, with publications jumping from one in 2022 to 36 in 2025 and 21 in the first half of 2026, signaling a maturing field that warrants systematic synthesis.

Classical conceptualizations of organizational culture (Cameron & Quinn, 2011; Schein, 2010) anchor the analysis, but the cultural specificity of GenAI requires additional constructs. Five concepts recur in the 2022–2026 literature: (1) AI readiness, the structural and cultural preparedness to absorb AI (Kelm & Johann, 2025; Pietsch & Mah, 2024); (2) digital culture, patterns of values and practices supporting technology-enabled innovation (Chu, 2023); (3) innovation culture, an orientation toward exploration and tolerance for failure (Burger-Helmchen, 2024); (4) AI literacy, the cognitive and practical capacity to evaluate and use AI responsibly (Lee & Park, 2024; Ng et al., 2025); and (5) psychological safety, the collective belief that experimentation will not invite social sanctions (Edmondson, 1999). These constructs are interrelated but have not been integrated into a single GenAI-specific construct. We therefore propose GenAI adoption culture, defined as the configuration of leadership vision, AI literacy and trust, psychological safety, ethical climate, and continuous-learning orientation that supports sustained, responsible, and value-creating use of generative AI by organizational members.

Four gaps motivate this review. First, dominant reviews emphasize technical capabilities (LLM performance, prompt engineering) or educational applications rather than workplace culture, leaving the cultural dimensions of organizational adoption under-theorized. Second, the cultural literature is fragmented across the five constructs above, and the bibliometric evidence in Section 3 will show that this fragmentation runs deeper still: the classical culture tradition is itself underused at the field's shared-citation core. Third, although bibliometric reviews have addressed adjacent AI phenomena such as deepfake crime risks (Al-Raggad, 2026) and Indonesia's digital labor transformation (Sulintang et al., 2024), no prior review has specifically examined GenAI adoption culture using science mapping combined with the TCCM framework recommended by Paul & Rosado-Serrano (2019). Fourth, the literature is geographically skewed toward East Asia, North America, and Western Europe, with emerging markets such as Indonesia and the wider ASEAN region underrepresented (only one Indonesian article in our final corpus). Practitioners also lack an integrative roadmap for designing interventions to foster a GenAI adoption culture.

These gaps, taken together, frame three research questions that guide the present analysis:
1) RQ1 (Thematic): What thematic clusters characterize the GenAI adoption culture literature published between 2022 and 2026?
2) RQ2 (Intellectual): How is the field structured intellectually in terms of co-citation foundations and bibliographic coupling research fronts?
3) RQ3 (Agenda): What research priorities should guide the next phase of inquiry, particularly in emerging-market contexts?

The study contributes in four ways. Methodologically, it is, to the authors' knowledge, among the first systematic bibliometric reviews to explicitly focus on the cultural dimensions of GenAI adoption in organizational settings and to combine performance analysis (bibliometrix), science mapping (VOSviewer), and TCCM synthesis within a single design. Conceptually, it proposes an integrative framework: Leadership Vision → AI Literacy and Trust → Psychological Safety → Ethical Climate → GenAI Adoption Culture → Productivity, Innovation, and Well-being. Practically, it derives a five-priority research agenda and a five-dimensional cultural diagnostic. Contextually, it foregrounds the under-representation of emerging markets, particularly Indonesia and ASEAN, that the present Indonesian author team is positioned to address.

2. Materials and Methods

The study adopts a three-layer review design integrating (i) bibliometric performance analysis following Click or tap here to enter text.; (ii) science mapping following Cobo et al. (2011) and (Zupic & Čater, 2015); and (iii) qualitative TCCM synthesis following Paul and Rosado-Serrano (2019). This hybrid bibliometric–systematic design parallels recent IJDNS reviews that combine performance metrics with qualitative synthesis (Destari et al., 2024; Falah et al., 2023), yielding both quantitative and conceptual perspectives on the field.

For the search itself, Scopus (Pranckutė, 2021) was chosen as the sole database for three converging reasons: (i) its comprehensive coverage of social-science and management journals relevant to organizational research; (ii) the structured cited-reference metadata required for co-citation and bibliographic-coupling analysis, which is more complete and consistently formatted in Scopus than in alternative sources (Mongeon & Paul-Hus, 2015); and (iii) the practical need for a single, internally consistent indexing schema to avoid cross-database duplication and metadata-conflict errors during bibliometric processing. The single-database choice is treated as an explicit limitation in Section 5, where a future multi-database extension (e.g., Web of Science and Dimensions) is recommended. The search was executed on 5 May 2026 at 16:15 WIB using the following query:

TITLE-ABS-KEY (("generative AI" OR "generative artificial intelligence" OR "large language model*" OR "LLM*" OR "ChatGPT" OR "GPT-3" OR "GPT-3.5" OR "GPT-4" OR "GPT-4o" OR "Gemini" OR "Claude" OR "Copilot" OR "foundation model*" OR "GenAI" OR "Gen-AI") AND ("organizational culture" OR "corporate culture" OR "workplace culture" OR "work culture" OR "organizational climate" OR "AI culture" OR "AI-ready" OR "AI readiness" OR "digital culture" OR "data culture" OR "innovation culture" OR "learning culture" OR "AI mindset" OR "digital mindset" OR "organizational value*" OR "workplace value*" OR "employee attitude*" OR "employee perception*")) AND PUBYEAR > 2021 AND PUBYEAR < 2027 AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO (SRCTYPE,"j"))

The query returned 257 records before automatic filters and 128 records after applying document-type, source-type, and language restrictions. The search string was iteratively refined through three pilot runs to balance recall and precision; the final formulation captured all seed articles independently identified through prior reading of the field (Chu, 2023; Ng et al., 2025; Jo & Bang, 2023), supporting its construct coverage.

Once the records were retrieved, inclusion required (I1) journal article; (I2) peer-reviewed; (I3) English; (I4) published 2022–2026; (I5) substantive treatment of GenAI; (I6) substantive treatment of organizational culture/climate; and (I7) organizational unit of analysis. Exclusion codes were defined as: E1 No GenAI focus; E2 Pure technical/ML application; E3 No organizational/work context; E4 Off-topic culture (heritage, political, media studies); E5 Education-only (treating schools as learning environments rather than organizations); and E6 Healthcare clinical only (without organizational-culture lens).

Screening then followed the PRISMA 2020 reporting guidelines (Page et al., 2021). After title-and-abstract screening of the 128 filtered records, 59 were excluded (E5 = 25; E1 = 9; E3 = 7; E2 = 6; E4 = 6; E6 = 6), yielding a final corpus of 69 articles (see Fig. 1). A notable methodological commitment was the exclusion of two highly cited records (Cao & Zhai, 2023, 49 citations; Maaz et al., 2024, 23 citations) on grounds of conceptual mismatch, demonstrating that citation impact did not override the organizational adoption-culture lens.

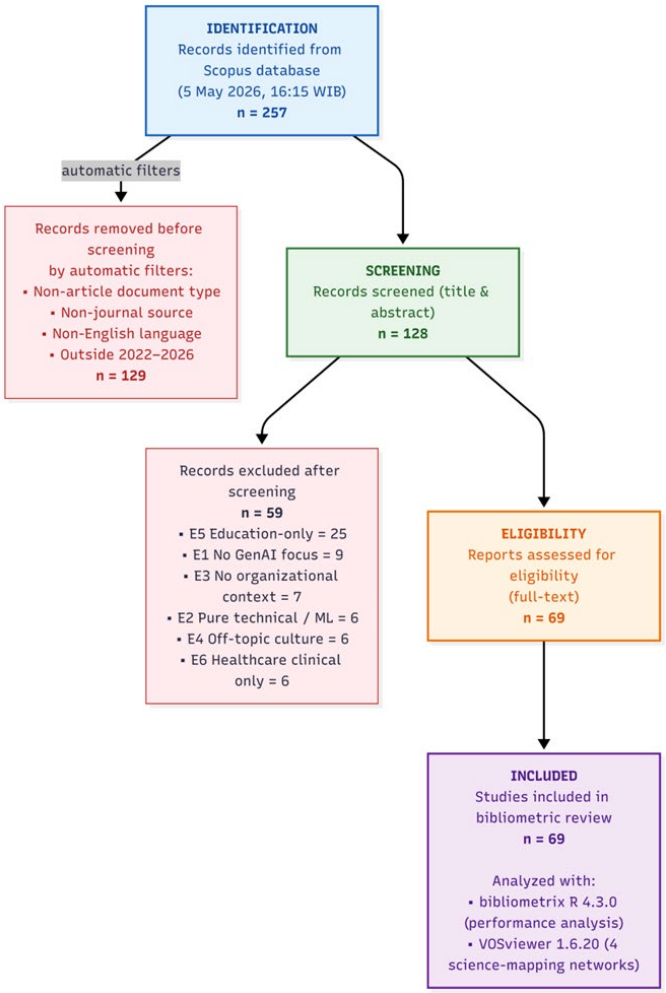

Fig.1. PRISMA 2020 flow diagram for record identification, screening, eligibility, and inclusion (n = 257 → 128 → 69)

Bibliographic records were exported from Scopus in BibTeX and CSV formats, capturing title, authors, affiliations, country, year, source, citations, abstract, author keywords, index keywords, and cited references. Records were cleaned in OpenRefine 3.8 through author-name normalization, country standardization, keyword lemmatization, and synonym clustering (e.g., the variants "generative AI", "genai", and "gen-ai" were merged).

Four networks were specified prior to analysis: keyword co-occurrence (minimum 3 occurrences), co-citation of references (minimum 3), bibliographic coupling among corpus documents (minimum 5 shared references), and thematic evolution split at 2024 to compare 2022–2023 (early phase) with 2024–2026 (growth phase). Thresholds were set below the conventional 5/5/10 cut-offs to reflect the small corpus (n = 69) and the field's early stage: higher thresholds produced sparse, fragmented networks in pre-analysis trials, whereas the chosen thresholds preserved stable clusters without admitting singleton noise. Cluster resolution was set to 1.0 (the default) and adjusted to 0.7–1.5 for interpretability (Van Eck & Waltman, 2010). Performance analysis was conducted using the bibliometrix package (version 4.3.0; Aria & Cuccurullo (2017) in R 4.3.0, with the biblioshiny graphical interface. Network visualization was performed using VOSviewer 1.6.20 (Van Eck & Waltman, 2010). Microsoft Excel and OpenRefine 3.8 were used for tabular processing. The qualitative layer was organized through the TCCM framework. Following Paul and Rosado-Serrano (2019), the top 15 articles, ranked by global citations and bibliographic coupling centrality, were synthesized across four dimensions: Theory (theoretical lenses), Context (sectors and geographies), Characteristics (variables and constructs), and Methodology (research designs). The 15-article cut-off corresponds to a natural break in the corpus citation distribution: articles ranked 16 and below each accumulated fewer than nine global citations, with diminishing analytical leverage for theory-and-methodology synthesis.

Reliability was supported by full compliance with PRISMA 2020, transparent exclusion coding (E1–E6), and dual screening by both authors. Initial inter-rater agreement on a random 20% sub-sample (n = 26 records) was 88.5% (Cohen's $\kappa = 0.79$, indicating substantial agreement per (Landis & Koch, 1977); the 11 disagreements were resolved through joint re-reading and discussion before the final corpus was locked. Reproducibility was preserved by archiving the cleaned BibTeX file, R scripts, and VOSviewer .txt network files.

3. Results

The final corpus of 69 articles spans 2022–2026 and is distributed across 65 sources, with 201 unique authors (11 single-authored documents) and 4,576 cited references, yielding an average of 9.04 citations per document and an annual growth rate of 114.07%. International co-authorship is 23.19%, with an average of 3 co-authors per document, and the mean document age is 0.93 years, confirming that this is an extremely recent and rapidly expanding field.

Table 1
Annual Scientific Production (2022–2026)

Year	Articles	Cumulative Share (%)
2022	1	1.4
2023	2	4.3
2024	9	17.4
2025	36	69.6
2026 (Jan–May)	21	100.0
Total	69	100.0

The trajectory exhibits a sharp inflection in 2025, consistent with the post-ChatGPT diffusion curve and the entry of organizational-behavior journals into the GenAI conversation, the most economical evidence that GenAI culture has become a topic researchers can no longer postpone.

Table 2
Top Source Journals (≥2 articles)

Rank	Source	Articles
1	International Journal of Advanced Computer Science and Applications	2
2	Journal of Innovation and Knowledge	2
3	Review of Managerial Science	2
4	TechTrends	2

The remaining 61 articles are distributed across 61 journals, indicating that the field is still pre-paradigmatic, with no dominant outlet yet established.

Table 3
Most Productive and Most Locally Cited Authors

Most Productive (Articles)	Most Locally Cited (Local Citations)
Arora, P. (2)	Chu, M.-N. (3)
Jo, H. (2)	Arora, P. (1)
Kato, T. (2)	Biggio, F. (1)
Koizumi, M. (2)	Callari, T. C. (1)
Li, K. (2)	Chan, E. K. C. (1)

No author exceeds two corpus articles, and Lotka's Law fitting ($\beta = 5.30$, $R^2 = 1.0$; KS $p = 0.964$) reveals a far steeper concentration than the canonical Lotka exponent of 2.0, signaling that authorship is currently dispersed and the field has not yet developed a stable cadre of repeat contributors.

Table 4
Top Countries by Corresponding Author

Rank	Country	Articles	SCP	MCP	MCP %
1	China	12	11	1	8.3
2	Germany	5	5	0	0.0
3	Korea	5	4	1	20.0
4	India	4	2	2	50.0
5	USA	4	3	1	25.0
6	Canada	3	1	2	66.7
7	Hong Kong	3	3	0	0.0
8	United Kingdom	3	1	2	66.7
9	France	2	2	0	0.0
10	Israel	2	2	0	0.0

SCP = Single-Country Publications; MCP = Multiple-Country Publications. Twenty-three countries contributed at least one article to the corpus; only the top ten are shown above. Indonesia ranks 23rd with one article (SCP = 1; MCP = 0). China dominates production volume but exhibits low international co-authorship (MCP = 8.3%), whereas Canada, the UK, and India display the highest cross-border collaboration (MCP ≥ 50%). Notably, Indonesia is represented by only one article, confirming the geographic gap motivating RQ3: dense scholarly attention is concentrated in East Asia and Western Europe. At the same time, the Global South, including Southeast Asia, remains largely unrepresented.

Table 5
Top Affiliations (≥2 articles)

Affiliation	Articles
Amrita School of Business (India)	3
Fiji National University	3
The Hashemite University (Jordan)	3
Arizona State University (USA)	2
Bar-Ilan University (Israel)	2
The Hong Kong Polytechnic University	2
University of British Columbia (Canada)	2
Sun Yat-Sen University (China)	2

Affiliation concentration nuances the country picture in Table 4. Although China leads in volume, no single Chinese institution dominates: contributions are distributed across regional universities, with Sun Yat-Sen the only repeat affiliation. The most productive institutions sit outside the East Asia/Western Europe core, Amrita School of Business (India), Fiji National University, and The Hashemite University (Jordan) each contribute three articles, signaling a quietly emerging Global South presence at the institutional level and reinforcing the case for deliberate Indonesian and ASEAN institution-building.

Table 6
Top 15 Most Globally Cited Documents (TCCM Core)

Rank	First Author, Year, Source	TC	TC/Year	NTC
1	Ng, D.T.K., 2025, Comput. Educ. AI.	99	49.5	12.29
2	Jo, H., 2023, Sci. Rep.	72	18.0	1.17
3	Lee, S., 2024, Curr. Psychol.	59	19.7	2.68
4	Rajaram, K., 2024, Bus. Horiz.	58	19.3	2.64
5	Chu, M.-N., 2023, IEEE Access	51	12.8	0.83
6	Zhao, H., 2024, J. Hosp. Tour. Manage.	33	11.0	1.50
7	Pietsch, M., 2025, Educ. Technol. Res. Dev.	32	16.0	3.97
8	Gómez Gandía, J.A., 2025, Technol. Forecast. Soc. Change	26	13.0	3.23
9	Shannaq, B., 2025, Bangladesh J. Multidiscip. Sci. Res.	23	11.5	2.86
10	Kelm, K., 2025, Corp. Commun.	16	8.0	1.99
11	Chateau, L., 2025, Media Cult. Soc.	14	7.0	1.74
12	Dong, E., 2024, Public Relat. Rev.	12	4.0	0.55
13	Callari, T.C., 2025, J. Workplace Learn.	12	6.0	1.49
14	Kato, T., 2024, Comput. Hum. Behav. Rep.	10	3.3	0.45
15	Giraldi, L., 2024, J. Inf. Sci.	9	3.0	0.41

TC = Total Citations; TC/Year = average citations per year; NTC = Normalized Total Citations. Ng et al. (2025) dominate the citation landscape with NTC = 12.29, followed by Pietsch and Mah (2025; NTC = 3.97), both treating educational institutions explicitly as organizations rather than as learning environments.

Turning from descriptive performance to thematic structure, the keyword co-occurrence map (minimum 3 occurrences; 21 items; full counting) yielded four interpretable clusters representing the field's present thematic structure:

Table 7

Keyword Co-occurrence Clusters

Cluster	Items	Representative Keywords	Proposed Theme Label
1 (red)	7	organizational culture, knowledge sharing, large language model, human, article, female, male	Culture & Knowledge Sharing
2 (green)	6	artificial intelligence, generative artificial intelligence, digital transformation, employee perceptions, information systems, technology adoption	Digital Transformation & Adoption
3 (blue)	5	decision making, job satisfaction, machine learning, natural language processing, sustainability	Decision-Making & Well-being
4 (yellow)	3	ChatGPT, generative AI, innovation culture	Chatbots & Innovation Culture

The cluster distribution in Table 7 reveals two high-intensity hotspots around artificial intelligence and generative AI/ChatGPT, while organizational culture sits at the periphery, tethered to knowledge sharing. Read as a map of attention, the picture is telling: culture is currently a connector between the field's bright spots rather than a research engine in its own right, a structural finding that directly speaks to RQ1. The co-citation analysis presented next deepens this signal rather than coincidentally repeating it: the keyword peripherality of organizational culture in Table 7 aligns with the absence of its classical references (Schein, Cameron, and Quinn) from the field's shared intellectual core in Fig. 2, a two-layer convergence that strengthens, rather than merely echoes, the diagnosis of cultural thinness.

The co-citation analysis of cited references (minimum 3 co-citations) reveals three intellectual sub-structures. The first is a Technology Acceptance cluster anchored by Davis's TAM lineage and Ajzen's Theory of Planned Behavior, with Nunnally's psychometric classic, Jarrahi's AI-at-work formulation, and Holmström's digital-transformation account orbiting the same core. The second is a Methodological–Applied GenAI cluster fusing PLS-SEM measurement classics (Sarstedt, Larcker, Podsakoff's common-methods critique, Bentler's fit-index work) with first-wave GenAI workplace empirics (Chen, Al-Khatib, Ahmed, Micu, and Dwivedi), reflecting the field's heavy reliance on variance-based structural equation reasoning. The third is a GenAI-in-Management cluster (Mariani's applications survey, Williams's AI essay, Lahmann's industry commentary) mapping the managerial framings that shaped early academic conversations (Fig. 2). Equally telling is what is missing: at the minimum-three threshold, classical organizational-culture references (Schein; Cameron and Quinn) and the dedicated AI-ethics literature do not reach the cut-off, an absence signaling that GenAI adoption-culture researchers are not yet routinely drawing on either the deep culture tradition or the responsible-AI literature as common reference points. The intellectual structure is therefore technology-acceptance dominant, methodologically homogeneous, and culturally thin, precisely the asymmetry that the integrative framework in Section 4 is designed to redress.

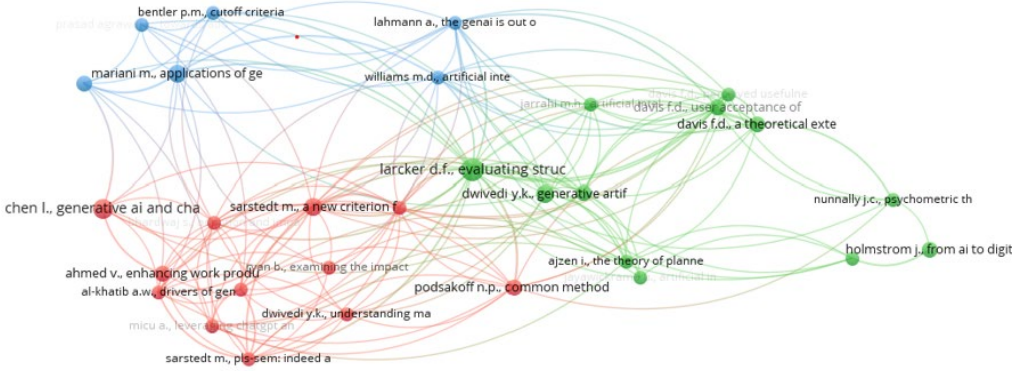

Fig. 2. Co-citation network of cited references, VOSviewer Network 1 (minimum 3 co-citations).

The bibliographic-coupling network (32 items; minimum 5 shared references) maps the research front, corpus articles most actively engaging with shared intellectual material. Five frontier clusters emerge:

1. Frontier 1, GenAI in workplace adoption (anchored by Chu, 2023 Kelm & Johann, 2025; Jo & Bang): adoption antecedents, employee perceptions.
2. Frontier 2, Educational organizations as adopters (anchored by Lee (Lee & Park, 2024; Pietsch & Mah, 2024; Ng et al., 2025) institutional adoption strategies in schools and universities treated as organizations.
3. Frontier 3, Strategic management & organizational performance (anchored by Gómez Gandía et al., 2025; Rajaram & Tinguely, 2024; Zhao et al., 2024) : GenAI as a driver of strategic transformation.
4. Frontier 4, Human-centered & ethical adoption (anchored by Alhusban et al., 2025; Callari & Puppione, 2025; Shannaq & Alabri, 2025): AI literacy, trust, ethical climate.
5. Frontier 5, Communication & public relations (anchored by Chateau et al., 2025; Dong et al., 2024): organizational communication of GenAI.

Frontiers 1 and 2 occupy the dense center of the map. At the same time, Frontier 4 forms a coherent peripheral cluster focused on ethics and human factors (Fig. 3), indicating that the human-centered research front is consolidating yet remains spatially distinct from the mainstream adoption literature. For the field to mature, the ethics frontier must migrate inward rather than stay parked at the edge.

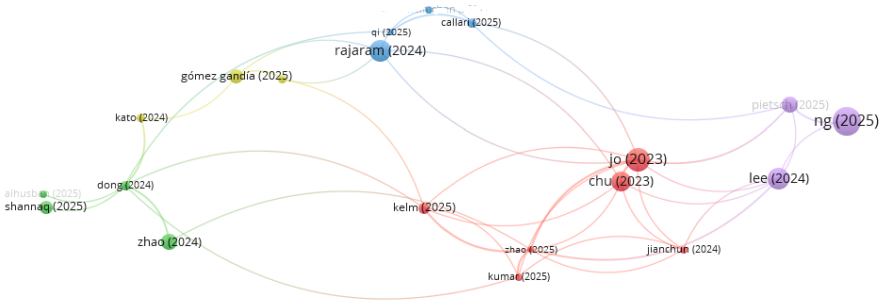

Fig. 3. Bibliographic coupling network of corpus articles, VOSviewer Network 2 (minimum 5 shared references; 32 items).

Finally, the thematic evolution analysis (split at 2024) reveals the trajectory of the dominant themes. In the 2022–2025 phase, three streams were active: artificial intelligence (largest), organizational culture (a small but distinct stream), and generative artificial intelligence. In the 2026 phase, two of these streams (artificial intelligence and generative artificial intelligence) grew substantially and absorbed elements of the organizational culture stream, which itself diminished in autonomy. The complementary strategic diagrams locate themes by centrality (relevance) and density (development):

1. Period 1 (2022–2025). Motor themes (high centrality + high density): organizational culture, job satisfaction. Niche themes: natural language processing, decision making, innovation. Basic themes: artificial intelligence, machine learning, and the workplace. Emerging/declining: ChatGPT, satisfaction, self-determination theory, employee engagement, public sector.
2. Period 2 (2026). Niche themes: generative AI, article, human. Basic themes: artificial intelligence, generative artificial intelligence, innovation culture, and technology adoption. Emerging/declining: sustainability.

The migration of organizational culture from a motor theme in 2022–2025 to absorption into basic themes in 2026 (Fig. 4) suggests a shift from an exploratory phase, in which culture was treated as a distinctive lens, toward a consolidation phase in which culture becomes quietly embedded in broader adoption narratives. This is a critical signal for RQ3: the cultural construct risks losing its theoretical sharpness unless researchers actively preserve it, a theme that becomes "basic" risks losing analytical visibility.

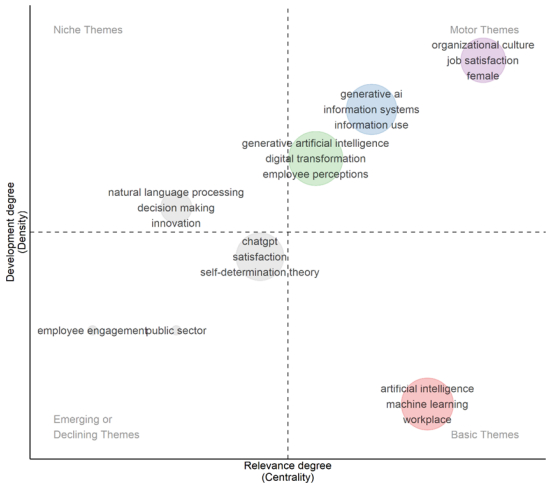

Fig. 4. Strategic diagrams, Period 1 (2022–2025) and Period 2 (2026), plotting themes by centrality (x-axis) and density (y-axis).

4. Discussion

Applying the Theory–Context–Characteristics–Methodology (TCCM) framework (Paul & Rosado-Serrano, 2019) to the 15 most globally cited and bibliographically central articles yields a finely textured map of how the field has been built. Table 8 condenses this map; the narrative below reads across the four dimensions.

Table 8

TCCM Matrix of the Top 15 Citation-Influential Articles

Article	Theory	Context	Characteristics	Methodology
Ng et al. (2025).	Schein's culture + AI literacy framework	K-12 schools, Hong Kong / East Asia	AI literacy, teachers' attitudes, institutional readiness, and knowledge sharing	Mixed-methods survey of teachers
Jo & Bang (2023)	Self-Determination Theory + Expectation Confirmation Model	Korean knowledge workers	Autonomy, competence, relatedness, continuance intention	PLS-SEM cross-sectional survey
Lee & Park (2024).	Social Cognitive Theory + Job Demands-Resources	Korean workplace employees	ChatGPT literacy dimensions, job satisfaction	Scale development (EFA / CFA)
Rajaram & Tinguely (2024).	Dynamic capabilities + strategic management	Global multinational corporations	Adoption roadmap, capability building, and leadership	Conceptual paper + multi-wave case studies
Chu (2023)	TAM + Resource-Based View	Taiwanese SMEs	Perceived usefulness, organizational performance	PLS-SEM quantitative survey
Zhao et al. (2024).	Innovation culture theory + Diffusion of Innovations	Chinese hospitality and tourism firms	Innovation culture, GenAI adoption, and firm performance	SEM cross-sectional survey
Pietsch & Mah (2025).	Schein's culture + multilevel organization theory	German schools	School culture configuration, AI implementation	HLM (hierarchical linear modeling)
Gómez Gandía et al. (2025).	AI readiness framework	Multi-country survey (Spain + EU)	AI literacy, organizational readiness	Cross-country quantitative survey
Shannaq & Alabri (2025).	Psychological safety (Edmondson)	Omani / Gulf-region organizations	Psychological safety, GenAI experimentation	Quantitative survey
Kelm (2025)	Strategic communication theory	European corporate communications	Communication strategies, leadership messaging	Qualitative case study
Chateau (2025)	Cultural studies + narrative theory	Media organizations, Western Europe	Organizational narratives, identity	Critical discourse analysis
Dong et al. (2024).	Public-relations theory + organizational communication	US organizations	Public communication, transparency, and ethical disclosure	Content analysis + survey
Callari & Puppione (2025).	Workplace learning + AI literacy	Italian / Southern European organizations	AI literacy, ethical climate, and learning routines	Multi-wave qualitative interviews
Kato & Koizumi (2024)	Self-Determination Theory + UTAUT	Japanese knowledge workers	Adoption antecedents, intrinsic motivation	Quantitative survey
Giraldi et al. (2024).	Information science + organizational communication	Italian / EU firms	Communication patterns, information flow	Mixed methods

Theory. The theoretical layer is dominated by borrowing. Approximately 40% of the core empirical papers rest on the Technology Acceptance Model (Davis, 1989) or UTAUT (Venkatesh et al., 2003), often paired with a culture or motivational lens (Chu, 2023; Jo & Bang, 2023). A second cluster privileges motivational and learning theories (Lee & Park, 2024; Callari & Puppione, 2025); a third turns to organizational-culture lenses anchored on Schein, Diffusion of Innovations, or psychological safety (Pietsch & Mah, 2025; Zhao et al., 2024; Shannaq & Alabri, 2025); and a fourth, emergent cluster draws on cultural studies and communication theory (Chateau, 2025; Kelm, 2025; Dong et al., 2024; Giraldi et al., 2024). Read alongside the co-citation map (Fig. 2), this architecture is diagnostic: classical culture references (Schein, Cameron, and Quinn) and dedicated AI-ethics works do not reach the minimum of three, while PLS-SEM measurement classics and applied GenAI empirics dominate. The field still borrows its theoretical apparatus rather than building one of its own, a technology-acceptance dominant, methodologically homogeneous, and culturally thin configuration that the integrative framework introduced below is designed to redress.

Context. Geographically, the corpus concentrates in East Asia (approximately 29%, led by China with 12 articles, followed by Korea with 5 and Hong Kong with 3), Western Europe (approximately 25%, anchored by Germany with 5 and the United Kingdom with 3), and North America (approximately 10%); Africa and Latin America are virtually absent, and a single Indonesian article represents Southeast Asia. Sectorally, educational organizations treated as adopting workplaces dominate the citation core (Ng et al., 2025; Pietsch & Mah, 2025; Lee & Park, 2024), with hospitality (Zhao et al., 2024), corporate communication (Kelm, 2025), media (Chateau, 2025), public relations (Dong et al., 2024), and general business strategy (Rajaram & Tinguely, 2024) supplying additional sectoral diversity. Traditional corporate contexts, manufacturing, finance, and professional services, remain comparatively understudied, leaving substantial room for evidence from Indonesian SMEs, ASEAN multinationals, and Southeast Asian public-sector organizations, whose high power distance, collectivist, and religiously plural premises differ meaningfully from the East Asian and Anglo-European settings that have shaped the literature so far.

Characteristics. Three variable families recur across the 15 core articles. Antecedents dominate, AI literacy (Lee & Park, 2024; Gómez Gandía et al., 2025; Callari & Puppione, 2025), perceived usefulness (Chu, 2023; Kato & Koizumi, 2024), trust in AI outputs (Shannaq & Alabri, 2025; Jo & Bang, 2023), leadership support (Pietsch & Mah, 2025; Rajaram & Tinguely, 2024), organizational readiness (Gómez Gandía et al., 2025), psychological safety (Shannaq & Alabri, 2025),

innovation orientation (Zhao et al., 2024), and ethical climate (Callari & Puppione, 2025; Chateau, 2025). Mediators include trust, motivation (the Self-Determination Theory triad of autonomy, competence, and relatedness), and engagement. Outcomes converge on adoption intention and actual use, but also extend to job satisfaction, organizational performance, knowledge sharing, innovation, and employee well-being. The most consequential observation, however, is what is missing: very few core articles theorize culture as a configuration, a bundle of interacting cultural attributes, rather than as a single variable. Pietsch and Mah (2025) come closest with their multilevel design; the framework introduced below responds directly to this gap by positing five interlocking cultural dimensions whose joint configuration, not whose individual presence, predicts sustained GenAI adoption.

Methodology. Cross-sectional quantitative surveys account for approximately 60% of core empirical papers, with partial least squares structural equation modeling (PLS-SEM) and covariance-based structural equation modeling (CB-SEM) as the workhorses (Chu, 2023; Jo & Bang, 2023; Kato & Koizumi, 2024; Zhao et al., 2024; Shannaq & Alabri, 2025), and scale-development designs adding rigor (Lee & Park, 2024). Qualitative case studies and interviews (Kelm, 2025; Callari & Puppione, 2025) supply approximately 20%, mixed methods (Ng et al., 2025; Giraldi et al., 2024) approximately 10%, conceptual essays (Rajaram & Tinguely, 2024) approximately 5%, and bibliometric reviews the remaining 5%. Multilevel designs are rare; only Pietsch and Mah (2025) employ hierarchical linear modeling. Genuinely longitudinal designs are virtually absent: only Rajaram and Tinguely (2024) and Callari and Puppione (2025) use multi-wave data, and even these fall short of the multi-year horizons that organizational culture change actually requires. This is the single most consequential methodological gap, because culture changes slowly and is observable only over time, yet the field's evidence base is overwhelmingly one-shot. The agenda articulated at the end of this section, therefore, prioritizes longitudinal multi-wave designs as the field's most urgent methodological investment.

Patterns across the citation core. Read horizontally across Table 8, two patterns stand out. First, the highest-impact and most theoretically integrative papers (Ng et al., 2025; Pietsch & Mah, 2025) cluster near the human-centered frontier of the bibliographic-coupling map, signaling that configurational thinking and ethical integration are surfacing together and that bibliometric impact rewards theoretical synthesis over single-stream contributions. Second, methodological sophistication tracks geography: East-Asian papers lean toward PLS-SEM surveys (Chu, 2023; Jo & Bang, 2023; Kato & Koizumi, 2024; Zhao et al., 2024), European papers toward case studies and multilevel models (Pietsch & Mah, 2025; Kelm, 2025; Callari & Puppione, 2025), and Anglo-American papers toward conceptual essays (Rajaram & Tinguely, 2024; Dong et al., 2024). The prominence of PLS-SEM measurement classics (Sarstedt, Larcker, Podsakoff, Bentler) in the Methodological–Applied GenAI sub-structure of Fig. 2 confirms that variance-based structural-equation reasoning has become the field's de facto methodological lingua franca, and the longitudinal and multilevel priorities articulated in Section 5 are explicitly directed against this empirical homogeneity. The Indonesian author team, sitting at the intersection of large Muslim-majority workplaces, collectivist work norms, and rapidly digitalizing economies, is positioned to contribute exactly the configurational, cross-cultural, longitudinal evidence the field currently lacks.

Building on the TCCM synthesis above and the four bibliometric layers (performance, keyword, co-citation, bibliographic coupling), the study proposes the following integrative framework for GenAI Adoption Culture (Fig. 5). The framework is presented as a propositional model derived from the bibliometric synthesis, not as an empirically validated structural model. Its construct relationships are theory-grounded but await direct empirical testing through PLS-SEM or multilevel designs in Indonesian and ASEAN samples, a priority articulated as Research Priority 2 below.

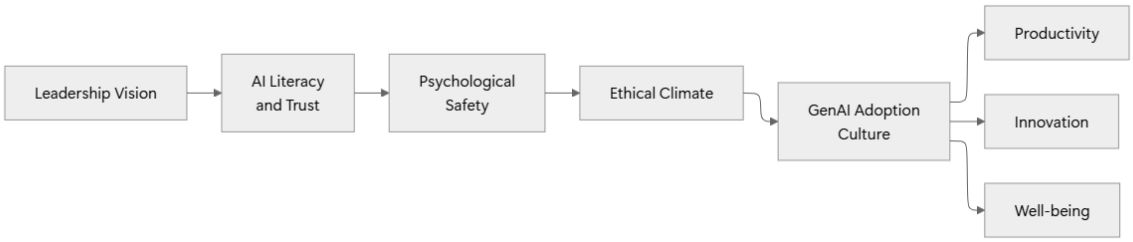

Fig. 5. Proposed integrative framework for GenAI adoption culture

The framework treats Leadership Vision as the upstream driver shaping AI literacy and trust, which in turn enables psychological safety for experimentation; an ethical climate stabilizes that experimentation, and the cumulative configuration constitutes GenAI adoption culture. Three downstream outcomes (productivity, innovation, and well-being) are theorized as differential consequences depending on which dimension is strongest. This structure is consistent with the centrality of organizational culture and job satisfaction as motor themes in 2022–2025, reframes GenAI adoption from an individual-level intention model into an organization-level cultural configuration for scholars, translates into a five-dimensional cul-

tural diagnostic (leadership communication, AI literacy training, psychological safety routines, ethical guardrails, continuous-learning rituals) for HR practitioners, and underscores the need for ethical-climate scaffolding to accompany infrastructure investments for policymakers.

The framework yields five testable propositions that operationalize the path model in Fig. 5 and can guide subsequent empirical work:

- P1. Leadership vision for GenAI is positively associated with organizational AI literacy and trust in AI outputs.
- P2. AI literacy and trust mediate the relationship between leadership vision and psychological safety for GenAI experimentation.
- P3. Psychological safety is positively associated with the strength of the organization's ethical climate around GenAI use, and this relationship is stronger in higher-collectivism cultural contexts (e.g., Indonesia, ASEAN) than in lower-collectivism settings.
- P4. The joint configuration of leadership vision, AI literacy and trust, psychological safety, and ethical climate constitutes a higher-order construct (GenAI adoption culture) that predicts sustained GenAI use beyond the variance explained by any single dimension.
- P5. GenAI adoption culture differentially predicts three downstream outcomes: productivity gains are most strongly predicted by AI literacy and trust, innovation by psychological safety, and employee well-being by ethical climate

From this framework, five priorities emerge as the most urgent items on the field's agenda:

1. Cross-cultural instrument development for GenAI adoption culture, validated across Hofstede dimensions.
2. Longitudinal multi-wave studies capturing how cultural configurations co-evolve with sustained GenAI use.
3. Middle-management bridge studies examining how supervisors translate leadership vision into psychological safety.
4. Emerging-market evidence, particularly Indonesia and ASEAN, to counterbalance the East-Asia/Western-Europe concentration documented in Table 4.
5. Ethics, bias, and responsible adoption as a distinct stream, building on the consolidating Frontier 4 cluster.

5. Conclusions and Research Agenda

This review has mapped, rather than declared, what GenAI adoption culture is. Across 69 articles published between 2022 and the first half of 2026, it has documented the cultural conditions that separate organizations in which generative AI takes root from those in which it is merely installed and then quietly abandoned. The volumetric evidence is unambiguous: an annual growth rate of 114.07%, 69 articles dispersed across 65 journals, and an authorship distribution (Lotka $\beta = 5.30$) far steeper than the canonical exponent together signal a pre-paradigmatic field whose contributors are still arriving through many disciplinary doorways at once. The structural evidence is equally consistent across three independent layers of the analysis: four clusters at the keyword surface, three sub-structures at the shared intellectual core, and five bibliographic-coupling frontiers at the active research front. The signal is common to all three layers. Organizational culture sits at the periphery of keywords; the classical culture references (Schein, Cameron, and Quinn) and the dedicated AI-ethics literature do not surface in the co-citation map at the minimum three-threshold; and the methodological palette has compressed around PLS-SEM measurement classics. The thematic-evolution analysis adds a temporal warning: organizational culture behaved as a motor theme during 2022–2025 but is now drifting toward absorption into generic adoption narratives, and unless researchers actively guard its theoretical sharpness, it risks losing analytical visibility.

These findings argue for a bridge rather than a choice. The integrative framework proposed in Section 4, Leadership Vision → AI Literacy and Trust → Psychological Safety → Ethical Climate → GenAI Adoption Culture → Productivity, Innovation, and Well-being, is deliberately parsimonious, precisely because the surrounding literature is already crowded with single-stream models that explain too little by trying to explain too much. From that bridge, five research priorities follow directly from the bibliometric gaps identified above: cross-cultural instrument development validated across Hofstede dimensions; longitudinal multi-wave designs that observe how cultural configurations co-evolve with sustained GenAI use; middle-management bridge studies tracing how supervisors translate leadership rhetoric into psychological safety; emerging-market evidence, particularly from Indonesia and ASEAN, to rebalance the East-Asia and Western-Europe concentration documented in Table 4; and a coherent ethics-and-responsible-adoption stream that integrates values, not merely processes, into the field's theoretical core. Three limitations qualify the present analysis: reliance on Scopus alone excludes Web of Science- and Dimensions-indexed work from the field of view; the English-only restriction underplays scholarship written in other languages; and the citation landscape for 2026 articles remains immature, penalizing the newest contributions even when their substantive importance is high. Subsequent reviews could braid multiple databases, widen the linguistic window, and revisit this corpus in 2027 or 2028 once the 2025–2026 cohort has settled into more stable citation patterns. The larger point of this synthesis, however, is the simplest: generative AI does not transform organizations because organizations transform their own infrastructure. Transformation occurs when leaders, employees, and the cultural patterns that connect them gradually adapt to integrate it over time.

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