The Determinants of Artificial Intelligence Capabilities; A Systematic Review

Abstract: *Purpose: This review examines determinants of organizational artificial intelligence (AI) capability while distinguishing antecedent conditions from constitutive resources, developmental processes, AI readiness, and downstream outcomes. Design/methodology/approach: A structured evidence map and construct-sensitive narrative synthesis were developed from targeted scholarly discovery. The accompanying register contains 56 distinct candidate bibliographic records, provisionally classified into antecedent/formation, constituent/measurement, and adjacent or unresolved categories. Eleven empirical publications are discussed as analytic exemplars, alongside four prior reviews. Title-term network, temporal-overlay, and density maps describe the candidate register. Findings: The empirical exemplars identify strategic and institutional conditions, learning processes, and resource-orchestration mechanisms relevant to capability formation. However, studies differ in their outcome definitions and analytic designs, preventing a valid pooled ranking of determinants. Originality/value: The review separates explanatory predictors from components used to measure capability and places visual title-term patterns alongside, rather than in place of, empirical evidence. Limitations: The candidate register is not a final included-study sample; a reproducible database-wide selection history and formal study-level risk-of-bias appraisal are unavailable. The synthesis therefore identifies defensible relationships and research priorities without claiming exhaustive systematic coverage.*

Keywords: organizational AI capability; determinants; systematic literature review; antecedents; organizational learning; resource orchestration; term co-occurrence.

1. Introduction

Artificial intelligence (AI) increasingly shapes organizational strategy and operations, yet technology acquisition alone does not establish the capability to use it effectively. Organizational AI capability coordinates technological infrastructure, data, human expertise, and managerial processes to create value. Mikalef and Gupta (2021) conceptualize this capability as a configuration of tangible, human, and intangible resources, emphasizing that technological ownership alone cannot explain sustained organizational competence. Similarly, Sjödin et al. (2021) demonstrate that capability development entails iterative interactions among data pipelines, algorithm development, organizational participation, and business-model adaptation. These perspectives distinguish resource possession from the routines needed to integrate and renew resources. They also expose a conceptual problem in the literature: resources included within the measurement of AI capability are sometimes discussed as though they were independent determinants of that same capability. For example, data quality, technical skills, and coordination may represent constitutive dimensions in one study but explanatory antecedents in another. Without distinguishing these analytical roles, evidence synthesis risks circular reasoning, inconsistent interpretation, and misleading conclusions about what actually drives capability formation. A determinants-focused review must therefore establish clear boundaries among organizational AI capability, AI readiness, technology adoption, and subsequent organizational performance.

Empirical research links AI capability formation with strategic orientation, organizational learning, and resource alignment, although evidence varies. Yang et al. (2026) examine digital orientation as an antecedent of organizational AI capability, investigating organizational learning and forgetting as mediating mechanisms and trust in AI as a moderating condition. Naz et al. (2024) position AI capability within an entrepreneurial-orientation and innovation pathway in the Malaysian hotel sector, illustrating strategic pathways to capability development. Alwakid and Dahri (2025) consider AI infrastructure, business integration, and proactive attitude in relation to AI capabilities among Saudi small and medium-sized enterprises. However, studies addressing related organizational phenomena cannot automatically be interpreted as tests of capability determinants. Jöhnk et al. (2021) examine organizational readiness for AI, while Jonak and Wodecki (2026) discuss governance and orchestration in AI deployment; both illuminate enabling conditions without directly measuring capability formation. Likewise, Ameen et al. (2024) investigate a combined AI-capability and strategic-agility mechanism, which should not be treated as an isolated capability outcome. Differences in constructs, measurement strategies, industries, and research designs complicate direct comparison. Cross-sectional associations cannot establish causal precedence. A rigorous synthesis must consequently distinguish tested antecedents from constituent resources, process explanations, contextual influences, and downstream effects rather than aggregating heterogeneous findings under a single determinant label.

Existing reviews address related but distinct questions. Chowdhury et al. (2023) synthesize AI capability resources in human resource management, Lee et al. (2023) examine organizational AI implementation, Gama and Magistretti (2025) review innovation capabilities and AI applications, and Ali and Khan (2025) focus on organizational AI readiness. Their syntheses inform conceptual boundaries but do not directly resolve which independent conditions explain the formation of an organizational AI-capability construct. Accordingly, the present study addresses four research questions: (RQ1) Which organizational and external conditions are modeled as antecedents of organizational AI capability, rather than as its constituent dimensions? (RQ2) How do resource-based, dynamic-capability, organizational-learning, attention-based, and socio-technical perspectives explain capability formation? (RQ3) Which contextual contingencies and divergent empirical findings can be distinguished without conflating different outcome constructs? (RQ4) How do measurement, study design, source coverage, and evidence quality constrain current conclusions and shape future research? The synthesis combines construct-role coding of empirical exemplars with a descriptive map of the wider candidate literature.

2. Theoretical background and review gap

2.1 Organizational AI capability and its boundaries

Organizational AI capability refers to a coordinated ability to select, combine, and exploit AI-specific resources in pursuing organizational objectives. Mikalef and Gupta (2021) operationalize this ability through a hierarchical configuration of tangible inputs, human skills, and intangible organizational resources. Their categories locate AI technology within a complementary system rather than at the center of a stand-alone diffusion narrative. Such a capability is not directly observed merely because a firm reports using an AI application. Adoption records an action or state of use; capability describes organized competence in mobilizing resources across business tasks, settings, and time. Readiness, in turn, concerns the organizational conditions supporting adoption and early deployment. A capability can build upon readiness, but readiness and capability need not be measured by the same instrument. Constitutive indicators differ logically from explanatory antecedents. If a construct contains access to data, technical knowledge, and change readiness, showing that this construct

predicts innovation does not prove that each individual dimension is an independent cause of capability formation. In formative measurement designs, indicator-to-construct weights are part of operational specification. This review therefore distinguishes a resource-as-component code from a resource-as-exogenous-predictor code. It also separates capability at the firm level from the capability of an individual employee to use AI, and from the capability of an algorithm to achieve benchmark accuracy. These safeguards are particularly important in multidisciplinary AI research, where the same ordinary word capability may denote radically different levels of analysis.

Capability can also be modeled in relation to learning and organizational transformation. Sjödin et al. (2021) explore the development of AI capabilities in six manufacturing firms, identifying data-pipeline, algorithm-development, and democratization capabilities that co-evolve with changes in business models. The qualitative evidence is important because it describes development as an iterative process involving customers, data operations, and ecosystem integration. Unlike a cross-sectional measurement model, such case evidence can illuminate sequences and organizational mechanisms. Nevertheless, it does not produce a generalizable coefficient for the effect of any single resource. The appropriate contribution is process theorizing rather than a fabricated numeric ranking of determinants.

2.2 Explanatory theoretical perspectives

Resource-based reasoning suggests that the sources of durable differentiation are not the mere possession of accessible digital tools but the organization-specific ways in which complementary resources are assembled. In AI settings, this directs attention to the joint configuration of data assets, skilled employees, managerial capabilities, and internal coordination. Fosso Wamba et al. (2024) examine resource configurations together with firm performance and the role of data-driven culture. Their approach illustrates how configurations can be analytically useful when individual resources are not assumed to operate independently. The theoretical inference remains bounded: configurations associated with high performance are not automatically evidence of the causal origins of an independently measured AI capability. Dynamic-capability perspectives supply a different unit of explanation: the organizational routines through which capacities are renewed as technologies, tasks, and markets change. The six-manufacturer study by Sjödin et al. (2021) is consistent with this process view because it examines scaling through co-evolutionary feedback between AI development and business-model innovation. The theory is particularly useful for interpreting why an organization with substantial technical inputs can still fail to scale them. A static inventory of resources may be necessary to describe the starting state; it does not capture the sequencing of integration, experimentation, and revision that converts resource availability into repeatable organizational competence.

Attention-based and organizational-learning accounts help explain how strategic orientation becomes capability-building activity. Yang et al. (2026) investigate digital orientation alongside organizational learning and forgetting as mediating processes, with trust in AI as a moderating condition. Cross-sectional self-report data support associations and modeled indirect paths but cannot by themselves establish temporal or causal ordering. Institutional perspectives are particularly relevant in the public sector. Drawing on 91 municipalities across Germany, Norway, and Finland, Mikalef et al. (2022) identify perceived financial costs, organizational innovativeness, governmental pressure, governmental incentives, and regulatory support as significant factors in a technology–organization–environment model. Their findings also do not support the proposed relationships involving citizen pressure and perceived value of AI solutions. The organizational and regulatory context must therefore be considered explicitly rather than inferred from private-sector studies. From a

complementary socio-technical perspective, Jonak and Wodecki (2026) propose an orchestration account that emphasizes governance, accountability, and process discipline. Because this account concerns readiness and deployment, it should not be pooled with coefficients for a separately measured organizational AI-capability outcome.

2.3 Prior systematic reviews and the research gap

Prior systematic reviews differ in their target constructs, empirical contexts, and definitions of AI-related capability. Table 1 compares four reviews that inform, but do not replace, a determinants-focused synthesis.

Table 1. Comparison with prior systematic reviews

Review	Review focus	Boundary for the current question
Chowdhury et al. (2023)	AI capability resources and AI-enabled HRM; multidisciplinary systematic/bibliometric synthesis	Functional HRM focus; organization-wide formation effects require separate assessment.
Lee et al. (2023)	Implementation of AI in organizations, including antecedents, barriers and consequences	Implementation antecedents cannot automatically be interpreted as formation determinants.
Gama & Magistretti (2025)	Innovation capabilities and applications; synthesis of 62 studies	Distinguishes capabilities enabling adoption from those enhanced after AI use.
Ali & Khan (2025)	Factors influencing organizational readiness for AI	Readiness remains conceptually distinct from mature AI capability.

3. Review methodology

3.1 Review design and evidence status

The review combines structured evidence mapping with a construct-sensitive narrative synthesis. Targeted discovery conducted on 29 October 2026 generated a register of 56 unique candidate bibliographic records: ten records from the initial source set and 46 additional leads identified through subsequent scholarly searching. Identifiers were checked by DOI or normalized title at the bibliographic-record level. The register is an exploratory search output, not a final sample of eligible studies. Eleven empirical articles are used in the text as illustrative evidence because their available publisher, institutional, or article records support the specific relationships discussed; four prior systematic reviews provide contextual comparison. No comprehensive search across Scopus, Web of Science, or comparable subscription databases was documented, and no record-by-record sequence of title/abstract screening, full-text eligibility, exclusions, or study-level quality appraisal accompanies the register. Accordingly, candidate counts, illustrative evidence counts, and final systematic-review inclusion counts are treated as distinct quantities. This reporting follows the transparency principles of PRISMA 2020 and PRISMA-S without treating an exploratory candidate register as a completed review flow (Page et al., 2021; Rethlefsen et al., 2021).

3.2 Search concepts and documented discovery

The search concepts combined organizational artificial intelligence capability with determinants, antecedents, resources, strategic orientation, learning, governance, public organizations, readiness, and related terms. Candidate records were assembled through targeted public scholarly search and

cross-checks of publisher records, institutional repositories, article identifiers, and reference lists. The working register retains article identifiers, publication years, titles, source links, provisional evidence roles, and notes on verification and access. Its 56 records span the publication years represented in the available source list; this does not establish comprehensive coverage of any prespecified period. Neither total database hits nor screened-article counts are inferred from exploratory web searches. The title-term maps in Section 4.6 summarize the same candidate register and are not used to determine empirical eligibility.

3.3 Eligibility and construct coding

The analytic unit for the final review is the individual empirical publication, not a title keyword, bibliographic lead, or review citation. Studies that explicitly model an organizational predictor of AI capability are categorized as direct antecedent evidence; those defining the elements of capability are categorized as constituent/measurement evidence; qualitative analyses of capability formation are treated as process evidence. Studies examining readiness, implementation, AI-enabled exploration, or downstream performance without a distinct capability-formation outcome are treated as adjacent or boundary evidence. These roles may overlap conceptually, but a publication is not counted twice in a unique-study denominator. The candidate register provisionally identifies 12 antecedent/formation leads, six constituent/measurement leads, and 38 adjacent or eligibility-unresolved records. These are initial bibliographic classifications, not final inclusion, exclusion, or quality judgments. Table 2 presents the interpretation rules used when discussing the empirical exemplars.

Table 2. Construct-based eligibility and analytic decisions

Evidence type	Appropriate analytic treatment	Inadmissible inference
AI capability predicted by entrepreneurial/digital orientation	Candidate direct-antecedent evidence	Do not infer time order from cross-sectional coefficients.
Human/data/technical resource indicators embedded within AI capability	Constitutive resource evidence	Do not convert formative weights into exogenous determinant effects.
Qualitative study of AI capability development	Formation-process evidence	Do not invent numerical effect sizes.
AI readiness, adoption intention or AI-enabled exploration	Separate boundary/context synthesis	Do not pool different dependent constructs as one outcome.
Prior systematic review	Research-gap and citation-chaining evidence	Do not count a review as an additional empirical firm study.

3.4 Screening, appraisal, extraction and synthesis

For the eleven empirical exemplars, information was compared on reported setting, study design, the dependent construct, antecedent or resource role, and the findings directly supported by accessible scholarly content. Publication abstracts and article text were not treated as interchangeable levels of evidence; unverified coefficients and subgroup comparisons were not inferred. Given differences in constructs and study designs, the synthesis is narrative rather than meta-analytic, and effect estimates are neither pooled nor ranked. No standardized design-specific risk-of-bias appraisal has been completed for the candidate register, and the present paper therefore does not assign risk-of-bias scores or evidence-certainty grades. These limitations restrict claims of comprehensiveness, causal direction, and comparative determinant strength, while allowing bounded discussion of specifically identified empirical relationships.

3.5 Candidate-title term mapping

Three descriptive visualizations were derived from the accompanying candidate-title map data. The underlying worksheet contains 27 labeled term nodes with supplied weights, cluster assignments, coordinates, and average-publication-year scores, together with 157 weighted links between terms. Network, overlay, and density views display this common term map. Node weights and link counts are used as supplied descriptive measures; the figures summarize title-term co-occurrence within the exploratory candidate register rather than author keywords, abstracts, citation relationships, or bibliographic coupling. These maps were reconstructed from the term data supplied in the workbook and are not analyses of citation, co-citation, or bibliographic coupling networks. Their role is to characterize the topical composition of candidate records, not to establish the frequency or effect strength of verified capability determinants.

4. Results and evidence synthesis

4.1 Scope of mapped evidence

The companion register contains 56 distinct candidate bibliographic records, comprising 12 provisionally antecedent/formation-oriented leads, six constituent/measurement leads, and 38 adjacent or eligibility-unresolved leads. None of those groups is a finalized included-study denominator. Table 3 instead presents eleven empirical publications used as analytic exemplars, including a direct public-sector antecedent model (Mikalef et al., 2022). Four prior systematic reviews are compared separately in Table 1, while two methodological references inform reporting practice. Because the available records differ in construct specification, access depth, and design, findings are interpreted for their specific evidentiary roles rather than treated as observations of a common effect.

Table 3. Empirical exemplars and their principal evidentiary roles

Citation	Study role	Evidence focus
Mikalef & Gupta (2021)	Constitutive measurement	Tangible, human and intangible AI-specific resource configuration; 143 technology managers.
Mikalef et al. (2022)	Direct antecedent / public sector	91 European municipalities; organizational, financial, governmental, and regulatory conditions.
Sjödin et al. (2021)	Formation process	Six manufacturing cases; data pipelines, algorithm development and AI democratization.
Naz et al. (2024)	Antecedent pathway	Entrepreneurial orientation and AI-capability mediation in Malaysian hotels; 260 responses.
Ameen et al. (2024)	Combined/boundary	AI capability coupled with strategic agility; China-based manager study.
Fosso Wamba et al. (2024)	Constitutive/configurational	AI resources, culture and performance in PLS-SEM and fsQCA analysis.
Alwakid & Dahri (2025)	Antecedent model described	Infrastructure, integration, proactivity modeled with AI capability in 250 Saudi SMEs.
Yang et al. (2026)	Direct antecedent model	Digital orientation; learning, forgetting, AI trust; 306 Chinese firms.
Jonak & Wodecki (2026)	Readiness/orchestration boundary	15 interviews; governance and behavior in effective deployment.
Jöhnk et al. (2021)	Readiness boundary	25 expert interviews; readiness factors, not observed capability effects.

Citation	Study role	Evidence focus
Atobishi & Nosratabadi (2026)	Exploration boundary	245 Saudi executives; sensing predicts AI-enabled exploration.

4.2 Tangible, human and intangible resources are not identical to antecedents

The organizational capability model of Mikalef and Gupta (2021) gives construct-development research an explicit resource architecture. Tangible inputs involve data, technologies and basic resources; human inputs include technical and business skills; intangible resources concern coordination, organizational change and risk-related capacities. The study provides empirical measurement evidence for these facets. The distinction between resource categories is substantively useful because it counters narrowly technological conceptualizations of AI capability. It would be methodologically incorrect, however, to enter all these facets into a thematic antecedent-frequency table as if each were an independently observed exogenous determinant. They already constitute part of the capability as measured in that study. The distinction is sharpened by Fosso Wamba et al. (2024). Their configurational analysis concerns how combinations of AI resources relate to firm performance, and the abstract identifies AI infrastructure as consequential in some performance configurations. This cannot legitimately be converted into the assertion that infrastructure is the strongest statistically supported antecedent of AI capability across firms. The dependent outcome differs, and the research design concerns configurations rather than isolating a formation effect. A methodologically sound synthesis uses such work to identify possible complementarities and to justify hypotheses about capability formation, while reserving stronger determinant language for studies that actually position capability downstream of a measured predictor.

Technical capacity is further situated in a developmental process by Sjödin et al. (2021). Their case-based findings emphasize data-pipeline and algorithm-development capabilities but also identify AI democratization. The last dimension points to mechanisms through which a narrowly specialist competence becomes distributed across organizational functions and linked with customer needs. The value of the case evidence lies in showing that capability development and business-model innovation are mutually adaptive activities. This interpretation cautions against simplistic linear models that presume an unchanged capability can be fully constructed before firms learn about its deployment setting. Yet the six-case qualitative design cannot establish a population-average causal effect for democratization or any other dimension.

4.3 Institutional and strategic antecedents and knowledge processes

A public-sector antecedent model is provided by Mikalef et al. (2022). Based on survey responses from 91 municipalities in Germany, Norway, and Finland, the authors examine technology–organization–environment factors in relation to organizational AI capabilities. They report significant relationships for perceived financial costs, organizational innovativeness, governmental pressure, government incentives, and regulatory support, whereas citizen pressure and perceived value of AI solutions are not supported as predictors. These findings locate capability formation within an institutional and organizational context and provide direct evidence beyond private-sector strategy models. Nevertheless, the cross-sectional municipal sample does not permit causal inference or unrestricted generalization to private firms. A complementary private-sector pathway is examined by Yang et al. (2026). Using 306 Chinese firms, that study links digital orientation with AI capability through organizational learning and forgetting, with trust in AI moderating associated paths. Its observed associations and configurational patterns suggest plausible knowledge-renewal mechanisms but do not eliminate reverse causation, common causes, or common-method concerns.

Naz et al. (2024) investigate an entrepreneurial-orientation pathway in 260 responses from Malaysian hotels, treating AI capability and big-data-analytics capability as mediating constructs in a co-innovation model. Environmental dynamism significantly moderates a relationship involving big-data analytics but does not significantly moderate the corresponding AI-capability–co-innovation link. That difference cautions against assuming uniform contextual effects across analytically distinct capabilities. Alwakid and Dahri (2025) examine a model incorporating AI infrastructure, business integration, and proactive attitude among 250 Saudi SMEs. Their study identifies candidate explanatory domains, but the material available for the present synthesis does not establish a verified, predictor-specific set of coefficients or significance decisions. These studies therefore contribute context-sensitive formation hypotheses rather than a comparable cross-study ranking of antecedent effects.

4.4 Governance, contextual contingencies and construct boundaries

The readiness literature brings governance and organizational alignment into view. Jöhnk et al. (2021) derive their organizational AI-readiness account from 25 expert interviews and organize relevant factors across strategic alignment, resources, knowledge, culture, and data. This identifies operational areas that a capability-building study should consider, yet the findings remain specifically about readiness. A firm may have strong readiness without having accumulated operational experience, just as a firm may exhibit narrow AI competence despite weak organization-wide readiness. Treating both as equivalent would conceal differences in outcome timing, measurement, and managerial action. Jonak and Wodecki (2026) use 15 practitioner interviews to argue that governance, accountability, process discipline and behavioral alignment have acquired increased salience in enterprise AI deployments. Their construct of AI orchestration emphasizes coordination of heterogeneous resources, routines and responsibilities. It is theoretically close to capability concepts based on resource orchestration, but the study develops and motivates a construct rather than estimating standardized antecedent coefficients for the Mikalef–Gupta AI-capability instrument. The material offers a valuable contextual proposition: as foundational technical inputs become more accessible, differentiated organizational capability may depend increasingly on how those inputs are governed and embedded. The proposition still requires comparative tests across organizations and time.

The combined-construct study by Ameen et al. (2024) offers a further caution for contextual analysis. The authors find that coupling AI capability with strategic agility is related to creative outcomes, with organizational ambidexterity and market orientations within their model and institutional support conditioning selected effects. These conclusions should be analyzed as relations involving a coupled mechanism, not proof that market orientation alone directly establishes an independent, unbundled AI-capability construct. The issue is especially relevant when a review attempts to map “drivers” from studies with heterogeneous dependent variables. A codebook that records the exact measured construct prevents superficially similar arrows from being counted together. The exploratory capability study of Atobishi and Nosratabadi (2026) is likewise informative but not equivalent. Its Saudi Arabian survey links organizational readiness and technology compatibility to sensing capability and, subsequently, AI-enabled exploration. The authors report a nonsignificant government-support pathway to sensing. These findings are valuable for broader dynamic-capability reasoning and supply evidence against unqualified expectations of external-policy support. However, AI-enabled exploration is not identical to a general organizational AI-capability construct. The study belongs in a boundary or sensitivity discussion until an explicit theoretical and operational equivalence is demonstrated.

4.5 Integrated analytical architecture

The evidence suggests four analytically distinct roles: (a) antecedent conditions, including strategic orientation and selected institutional or integration-related factors; (b) organizational processes, including learning, forgetting, and orchestration; (c) tangible, human, and intangible resources that constitute AI capability in some measurement models; and (d) adjacent or downstream outcomes, including adoption, exploration, innovation, and performance. A particular factor, such as governance or organizational knowledge, may be positioned differently across studies depending on the construct definition and measurement design. The framework organizes relationships that warrant comparative investigation; it does not assert a universal causal sequence, quantify determinant prevalence, or combine non-equivalent outcome measures.

4.6 Descriptive title-term maps of the candidate literature

Figures 1–3 retain the network, temporal-overlay, and density views derived from the 56-record candidate register. The underlying map comprises 27 recurring title terms and 157 weighted term links. Its prominence and proximity patterns describe co-occurrence in the candidate titles, not the number of eligible systematic-review studies or the magnitude of causal determinants. In particular, a high-frequency term such as performance need not describe a predictor of AI capability: many candidate articles examine performance as an outcome. The figures complement the construct-role synthesis and should be interpreted as descriptive visual summaries of the search leads.

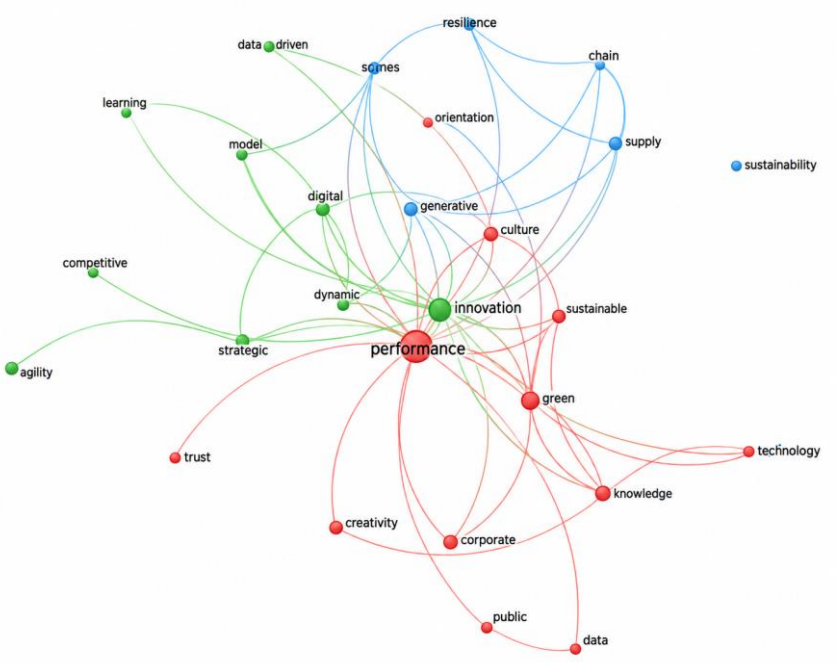


Figure 1. Network map of recurring title terms in the 56-record candidate register. Node prominence, weighted links, and cluster colors represent the supplied term-mapping data.

In Figure 1, performance and innovation occupy central positions among the mapped candidate-title terms. Connections to digital, strategic, green, and other terms indicate topical co-occurrence within the register, while more peripheral terms describe narrower strands of the candidate literature. Network centrality is not evidence that a term is an empirically established antecedent: performance is commonly treated as a dependent outcome, and the candidate records have not all passed full-text eligibility screening.

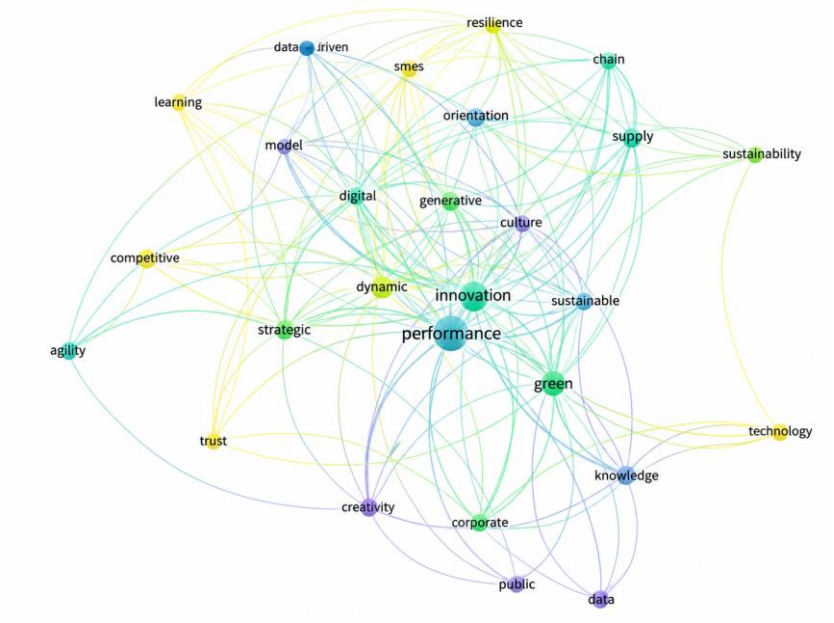


Figure 2. Temporal overlay of the same candidate-title term network. Color variation represents the average publication-year scores supplied for the mapped terms.

Figure 2 overlays term-level average-publication-year scores on the same network. It allows visual comparison of relatively earlier- and later-associated terms within this particular source register, rather than measuring the growth rate of research activity or demonstrating a general historical shift across the full field. The temporal pattern is subject to the coverage and publication-year composition of the 56 candidate records.

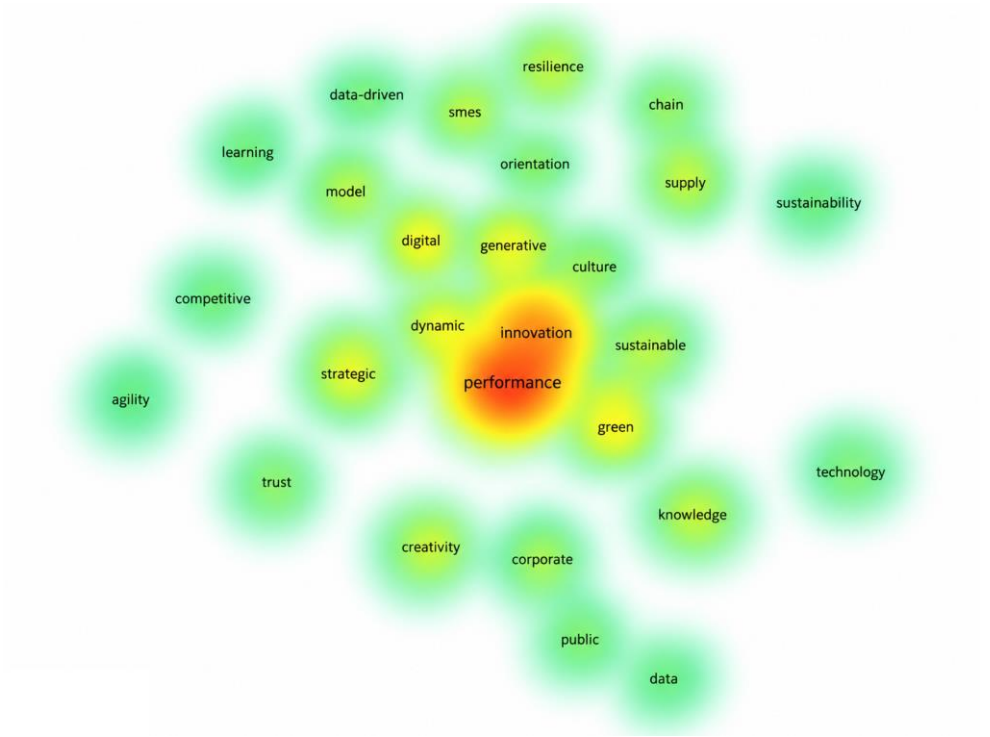


Figure 3. Density view of recurring title terms in the candidate register. Warmer areas indicate stronger concentration under the supplied term-weight and mapping configuration.

Figure 3 concentrates around performance and innovation, with other prominent areas involving digital, strategic, generative, and green themes. The density plot reflects title-term weights and spatial proximity within this candidate set. It cannot be used to conclude that specific determinants have stronger empirical support, especially because many candidate studies investigate organizational outcomes or adjacent AI-related constructs rather than capability formation itself.

5. Discussion

The first research question concerns conditions empirically modeled as antecedents of organizational AI capability. Mikalef et al. (2022) offer a direct public-sector model in which selected financial, organizational, and institutional factors are associated with capability in European municipalities. Yang et al. (2026) examine digital orientation, organizational learning, and forgetting in firms, whereas Naz et al. (2024) place AI capability within an entrepreneurial-orientation and co-innovation pathway. Alwakid and Dahri (2025) model infrastructure and organizational integration-related domains, although predictor-specific effect evidence is not equally accessible. These investigations illuminate possible antecedent mechanisms without establishing a universal causal ordering. In contrast, Mikalef and Gupta (2021) treat tangible, human, and intangible resources as capability components, and Sjödin et al. (2021) investigate iterative capability development. Keeping components and mechanisms separate from predictors is essential for valid synthesis. The candidate-title maps additionally show an emphasis on performance and innovation terms, but those descriptive frequencies do not count or rank empirically supported capability determinants.

Concerning the second research question, the findings suggest that organizational AI capability formation can be interpreted through complementary theoretical perspectives, each explaining a distinct dimension of the development process. Resource-based reasoning emphasizes the importance of combining technological infrastructure, organizational knowledge, employee expertise, and intangible resources into configurations that support organizational competence. Dynamic capability theory extends this explanation by emphasizing adaptation, resource reconfiguration, and the continuous renewal of competencies in response to technological and environmental changes. The findings of Sjödin et al. (2021) are particularly relevant because they illustrate how AI capability development interacts with organizational learning and business-model innovation through iterative processes. Organizational learning and attention-based perspectives provide additional explanations for how strategic priorities may be translated into organizational capabilities, as illustrated by the relationships examined by Yang et al. (2026). Furthermore, socio-technical and institutional perspectives draw attention to governance arrangements, accountability, workforce participation, and environmental conditions that influence the organizational embedding of AI technologies. Jöhnk et al. (2021) identify organizational readiness factors that may facilitate AI implementation, while Jonak and Wodecki (2026) emphasize the role of orchestration in aligning technological resources with organizational processes. However, readiness, orchestration, and established AI capability remain analytically distinct constructs. Accordingly, theoretical integration should not imply that all perspectives explain identical relationships or have received equivalent empirical support. Rather, their collective contribution lies in clarifying how organizational resources, strategic orientations, learning mechanisms, and contextual conditions may interact throughout capability development.

The third research question concerns differences in context and estimated relationships. The municipal model of Mikalef et al. (2022) reports unsupported citizen-pressure and perceived-value relationships while retaining significant effects for other organizational and institutional predictors. Naz et al. (2024) report that environmental dynamism does not significantly moderate the AI-capability–co-innovation path in the same way as a big-data-analytics pathway. Atobishi and

Nosratabadi (2026) find a nonsignificant government-support relationship to sensing in an AI-enabled-exploration model. These observations involve different predictors, outcomes, and contexts and are not opposing estimates of a single comparable effect. Cross-sectional data further allow reverse causation, common influences, and self-report bias. Consequently, meaningful contrasts require construct-equivalent models and context-sensitive interpretation, not unqualified frequency counts or pooled coefficients. The fourth research question addresses confidence and transferability. The candidate register supplies 56 bibliographic leads, but its provisional categories do not constitute a reproducibly screened body of included studies. The absence of a full search-export history, documented exclusion decisions, and formal design-specific risk-of-bias judgments therefore limits systematic coverage and certainty. In addition, empirical studies operationalize organizational AI capability differently: some embed resources as dimensions of capability, while others test strategic or institutional factors as explanatory predictors. Future research should clearly distinguish these construct roles, assess discriminant validity, collect longitudinal and multi-source evidence, and compare contexts using equivalent measurement. A subsequent comprehensive review would additionally benefit from database-specific archived search strategies, full-text eligibility decisions, and quality appraisal aligned with study designs. The present findings offer an evidence-bounded synthesis rather than a complete prevalence estimate or causal ranking of determinants.

The findings also offer practical implications for organizational managers and policymakers seeking to strengthen AI-related competencies. Organizations should evaluate AI capability development in relation to strategic objectives, organizational readiness, resource integration, and implementation responsibilities rather than relying exclusively on technology procurement or application adoption. Investments in data infrastructure, technical expertise, employee development, and governance mechanisms should be coordinated with clearly defined operational requirements and organizational learning processes. Sjödin et al. (2021) demonstrate the importance of iterative capability development, suggesting that organizations may benefit from continuously aligning technological initiatives with evolving business models and operational practices. Management should also establish appropriate accountability structures, performance-monitoring procedures, and mechanisms for evaluating the organizational consequences of AI implementation. From a policy perspective, external incentives and technology-support programs should be assessed according to their contribution to organizational learning, integration, and sustained capability formation rather than technology accessibility alone. Although Atobishi and Nosratabadi (2026) report a nonsignificant government-support relationship within a specific sensing-capability model, this finding cannot justify general conclusions about the effectiveness of institutional support across organizational settings. Instead, it reinforces the need for context-sensitive policy evaluation and stronger empirical designs. Overall, the synthesis suggests that organizational AI capability emerges through interactions among strategic priorities, complementary resources, organizational learning, and institutional conditions. Establishing which relationships consistently influence capability formation will require more comparable constructs, stronger longitudinal evidence, and systematic assessment of methodological quality.

Table 4. Evidence-derived future research agenda

Observed uncertainty	Research question	Appropriate design
Antecedents overlap with capability indicators	Which exogenous variables predict future AI capability above its constitutive resources?	Longitudinal multi-source organizational panels
Learning and forgetting are concurrent in cross-sectional models	What is the sequence through which orientation becomes capability?	Three-wave process study with qualitative tracing

Observed uncertainty	Research question	Appropriate design
Governance spans readiness, orchestration and deployment	When is governance a prerequisite, determinant, constituent or moderator?	Multisector comparative mixed-methods design
Organizational and institutional contingencies differ by setting	Under which policy conditions do external incentives translate into real competence?	Quasi-experiment or comparative longitudinal field study
Heterogeneous measures preclude pooled estimation	Can a harmonized organizational AI capability scale show equivalence across sectors?	Measurement-invariance and construct-validation program

6. Conclusion

Organizational artificial intelligence capability represents a distinct organizational competence that extends beyond technology adoption, organizational readiness, AI-enabled exploration, and subsequent performance outcomes. The reviewed evidence identifies several potential determinants of AI capability formation, including institutional and organizational conditions, digital and entrepreneurial orientations, organizational learning, knowledge renewal, and resource integration. These determinants operate through different organizational mechanisms and vary across institutional, industrial, and geographical contexts. The findings further emphasize the importance of distinguishing tangible, human, and intangible resources that constitute AI capability from independently examined antecedents influencing its development. Complementing the qualitative synthesis, three bibliometric visualizations derived from a broader set of 56 candidate publications illustrate thematic connections, temporal patterns, and concentrations within the research landscape. However, these descriptive patterns do not independently establish causal relationships or determine the relative importance of individual determinants. Overall, the review develops an integrated, construct-sensitive framework that clarifies the organizational conditions and processes associated with AI capability formation, highlights contextual and methodological differences across existing studies, and identifies priorities for future empirical research.

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