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AI USE-CASE PRIORITIZATION MODELS FOR BUSINESS AND TECHNOLOGY LEADERS: AN INTEGRATIVE REVIEW AND DEPENDENCY-AWARE PORTFOLIO FRAMEWORK

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ABSTRACT

As organizations expand their investments in generative AI, traditional AI, and machine learning, candidate initiatives increasingly compete for the same capital, data assets, leadership attention, technical talent, infrastructure, and governance capacity. This review examines how peer-reviewed journal research published between 2015 and 2025 informs the ranking, selection, sequencing, and governance of organizational AI use cases. The review is oriented primarily toward generative AI initiatives while retaining applicability to traditional AI and machine-learning use cases, particularly where earlier predictive and analytical investments shape the readiness and expected value of newer generative applications. There is not yet a well-established and coherent model named specifically AI use-case prioritization in literature. Rather, the knowledge is distributed across AI readiness, business value, AI-enabled decision-making, dynamic capability, sociotechnical implementation, adoption, governance and organizational transformation. The review identifies four dimensions of prioritization: strategic value, technical feasibility, organizational readiness, and risk-governance exposure. Evidence concerning high-value AI projects indicates that value estimation alone is insufficient for successful prioritization; the goals and objectives of the use cases must align with data maturity, the operating model, human oversight, scalability, and accountability systems. Persistent gaps include limited longitudinal evidence, underdeveloped measures of risk-adjusted value, insufficient portfolio-level evidence, and weak connections between AI governance and investment sequencing. The article synthesizes these distributed findings into the Integrated AI Prioritization and Sequencing Framework (IAPSF), a review-derived conceptual framework that integrates initiative-level assessment with portfolio-dependency analysis. The IAPSF is intended as an executive decision architecture rather than an empirically validated scoring model.

Keywords: AI governance; AI readiness; Business value; Generative AI; Machine Learning; Portfolio Prioritization; Sociotechnical Systems

1 INTRODUCTION

AI use case prioritization models for business and technology leaders solve a real-world and theoretical problem that is increasingly relevant as businesses transition from individual projects to collections of AI-powered products, processes, and decision-making systems. The question is therefore not only which forms of AI can create value, but also which proposed initiatives merit immediate investment, which require further capability development before deployment,

which should be deferred until prerequisite capabilities or controls are established, and which should not proceed because of technical uncertainty, ethical exposure, or organizational mismatch. It is not yet a standard model family, although the issue has garnered many scholars' attention. Instead, the relevant literature is distributed across several bodies of literature on organizational readiness, managerial support, organizational value creation, adoption of AI, sociotechnical governance, and AI-based decision structures.

In this general category, the review is focused mainly on generative AI projects given their current scale and prevalence across a variety of organizational functions, which has increased the urgency of executives' need for a structured prioritization approach. However, the underlying literature and the proposed framework also encompass traditional AI and machine-learning initiatives, especially where existing prediction, classification, optimization, recommendation, or anomaly-detection capabilities provide prerequisites for generative AI deployment. Throughout this article, the term 'AI initiatives' therefore uses generative AI as the principal contemporary application context while retaining traditional AI and machine learning within the analytical scope.

Through the study of AI-driven decision-making, it becomes clear that prioritization needs to go beyond traditional project ranking. AI initiatives have the potential to affect the authority of decisions, imbalances in information power and the distribution of accountability among algorithmic systems and humans [1]. This differentiates the prioritization of AI use cases from the use of other technology projects as the selection of an AI use case can affect managerial judgment, operational procedures, and control processes. Moreover, the automation–augmentation paradox suggests that the value of AI is less about its automation capabilities and more about its reinforcing and complementing role to human action [2]. In that case, a well-performing use case can be strategically weak because it challenges human expertise, can lead to brittle workflows, or may not be governed in a way that assigns accountability and responsibility.

AI research that aims to impact decisions also highlights the importance of data quality, explainability, organizational learning, and managerial trust [3]. These factors are important because an initiative that appears promising in principle may fail when the required data foundations, decision rights, or domain knowledge are absent. The strategic AI reviews also show that AI is not just part of a digital transformation, but the competitive value of the organization is determined by aligning algorithms, processes, and organizational structures and developing capabilities [4]. This implies that the adoption of AI should be considered within the context of investments in sociotechnical systems as opposed to analytics projects.

This is confirmed by the business value literature. Complementary assets, in addition to technical infrastructure, managerial capacity, a skilled workforce, process redesign and absorptive capacity, are also crucial to AI value creation [5]. This is a sequencing issue for the business and technology leaders. In larger companies, such as financial services firms, few candidate AI projects start from a similar capability baseline. Some data pipelines, legacy machine-learning models, workflow integrations, domain-specific knowledge, monitoring workflows, and governance policies can significantly influence the viability and benefits of future generative-AI projects [5, 7, 8, 16, 18]. For instance, continued investment in fraud analytics can produce well-established transaction data, investigation workflows, monitoring procedures, and model-risk controls. These inherited assets can improve the prospects of new generative AI applications within fraud operations and can also support adjacent use cases, such as customer-service assistance for fraud-related inquiries. Prioritization should therefore assess not only the stand-alone attractiveness of an initiative but also its dependence on existing capabilities and its potential to create reusable assets for related initiatives.

The relevance of AI use case prioritization is quite broad. Information systems research provides constructs of digital capability, adoption, governance and business value. Strategic management contributes three perspectives portfolio logic, competitive positioning, and dynamic capabilities theory. Operations and analytics research provides feasibility assessment, experimentation, and model performance evaluation. Organizational studies provide knowledge regarding aspects of work redesign, authority, learning and sociotechnical change. However, these research streams are not closely integrated. Many existing studies focus on the adoption of AI, AI capability or AI value creation, and the managerial process of ranking competing AI use cases has received limited attention directly.

This article adopts an integrative review approach and examines identifiable peer-reviewed journal articles published between 2015 and 2025. Studies were retained when they addressed at least one construct directly relevant to the comparison, ranking, gating, or sequencing of organizational AI initiatives: strategic or business value, technical feasibility, organizational readiness and adoption, sociotechnical implementation, governance and risk, or portfolio interdependence. Purely technical studies concerned only with algorithmic performance, non-peer-reviewed sources, and publications without an organizational or managerial connection to use-case prioritization were outside the review scope. The selected studies were organized into thematic clusters and coded according to their methodological approach, principal contribution, limitations, and coverage of the four prioritization dimensions.

Building on the reviewed literature, this article proposes the Integrated AI Prioritization and Sequencing Framework (IAPSF) as a review-derived conceptual decision architecture. The framework integrates initiative-level assessment

with portfolio-level sequencing to distinguish initiatives suitable for scaling, piloting, prerequisite capability development, deferral, redesign, or rejection. It does not represent an empirically validated scoring model; rather, it translates recurring constructs from the reviewed literature into a transparent structure for executive comparison.

2 LITERATURE REVIEW

There are four thematic areas that form the basis of the literature on AI use-case prioritization: business value and capability, organizational readiness and adoption, sociotechnical implementation and strategic governance. These clusters do not constitute a unified algorithmic framework for prioritizing AI use-cases, but they provide complementary insights to consider when deciding which use cases to invest in. The business value cluster suggests that the objectives of all AI initiatives should be assessed on measurable outcomes rather than technical complexity. Wamba-Taguimdje et al. examine firm performance and transformation projects done with the help of artificial intelligence, proposing that the extent of transformation and managerial buy-in, together with the process influence, determine value realization [6]. Mikalef and Gupta take a capability-based perspective in which the capability of AI is considered as a combination of resources (tangible, human, intangible) that influence creativity and performance, rather than as a binary indicator of possession [7]. In terms of prioritization, this means that expected returns are not the only consideration for candidate use cases when determining their priorities, in addition to considering the capabilities of the organization.

The readiness and adoption literature highlights the need for prioritization, which relies on implementation capacity. Jöhnk et al. list organizational AI readiness factors as strategic alignment, data availability, skills, culture and governance [8]. This research is directly applicable because if readiness is not taken into account, then prioritization models can systematically over rank ambitious but infeasible initiatives. The study by Chatterjee et al. [9] investigates the adoption of AI technologies from the point of view of technology acceptance and technology–organization–environment. They argue that the level of acceptance of AI relies on a number of factors such as perceived usefulness, compatibility, external pressure and organizational support [9]. Readiness is implicit in these studies; the credibility of a value estimate is only gained once feasibility and adoption conditions are taken into account.

The third cluster addresses sociotechnical implementation and value destruction. Canhoto and Clear present a procedure for evaluating the potential for value destruction in AI/machine learning based applications, claiming that "AI systems can destroy value if they are not congruent with the situation, data, or perceptions of the stakeholders" [10]. Makarius et al. offer a perspective on the sociotechnical nature of introducing AI into organizations, emphasizing the interactions among the technology, people, tasks and structures [11]. Jarrahi takes this idea further and shows how in the context of an organization's decision-making AI can assist human judgment in scenarios where uncertainty and tacit knowledge and interpretation of context is significant [13]. Faraj et al. also demonstrate how learning algorithms have the power to change organizing in ways that are opaque, continuous, and different from what is currently in control [14]. This research calls into question exclusive financial-based prioritization and advocates a risk-adjusted, work-system-based approach.

The fourth cluster focuses on strategic management, information systems governance and transformation. Brock and von Wangenheim warn against illusory expectations and highlight practical lessons in AI leadership, such as framing problems and scaling iteratively [12]. Collins et al. provide a mapping of AI in information systems research and recognize fragmentation in technical, organizational and management areas [15]. Berente et al. define AI management as different from conventional information systems management because AI systems learn, adapt and deliver results that are not completely predetermined at design time [16]. Keding's research on AI and strategic management demonstrates its impact on strategic management, strategic processes, and the cognitive abilities of managers [17]. Mikalef et al. [18] build on the capability argument by associating AI capabilities with organizational performance in inter-organizational settings. Collectively, this cluster indicates that the leaders should possess portfolio models that can address strategic option value, capability building in organizations, risk governance and learning.

Table 1 presents an overview of the studies reviewed that are most relevant to the AI use-case prioritization. The literature indicates that building blocks exist but limited evidence on integrated prioritization is available. Most studies test determinants, capabilities, readiness conditions or organizational consequences, but not complete prioritization models in multiple AI use cases.

Table 1: Summary of key findings

Ref	Focus	Key Findings
[6]	AI-enabled transformation and firm performance	AI value depends on transformation scope, process change, managerial alignment, and performance linkage.
[7]	AI capability and organizational performance	Tangible, human, and intangible AI resources jointly affect creativity and performance.
[8]	Organizational AI readiness	Readiness requires strategy, data, skills, culture, infrastructure, and governance alignment.
[9]	AI adoption in manufacturing	Adoption is shaped by perceived usefulness, compatibility, organizational support, and environmental pressure.
[10]	AI value destruction risk	AI initiatives can destroy value through poor contextual fit, data misalignment, and stakeholder harm.
[11]	Sociotechnical AI implementation	Effective implementation requires alignment among people, tasks, structures, and AI systems.
[12]	Realistic AI leadership	Pragmatic AI leadership favors clear problem framing, disciplined experimentation, and scalable deployment.
[13]	Human–AI decision complementarity	AI creates value when machine prediction and human contextual judgment are appropriately combined.
[14]	Learning algorithms in organizing	Algorithmic opacity and adaptability reshape work, control, and accountability.
[15]	AI in information systems research	The field remains fragmented across technical, organizational, and governance concerns.
[16]	Managing AI	AI management differs from conventional IT management because learning systems create dynamic control issues.
[17]	AI and strategic management	AI influences strategy formation, competitive analysis, cognition, and organizational capability.
[18]	AI competencies and performance	AI-related competencies mediate performance effects through organizational and market-facing capability.

The table shows three gaps in the current knowledge base. The first is that most studies deal with prioritization inputs on a separate basis. However, the concepts of value, readiness, risk, and capability are distinct — and there is insufficient research on integrated scoring and sequencing models. Second, empirical designs tend to be at the level of adoption or performance, whereas AI use-case portfolios are often assessed at the initiative level. Third, risk and governance are discussed conceptually rather than operational prioritization criteria. These constraints result in a gap between theory and practice in the implementation of executive decisions.

3 METHODOLOGY

This review was conducted using a structured, narrative integrative review approach. Searches were performed with various combinations of terms covering artificial intelligence, generative AI, machine learning, use-case prioritization, business value, technical feasibility, organizational readiness, governance, risk, and portfolio sequencing. The databases were chosen to be multidisciplinary in management, information systems and technology research. Records were initially reviewed based on their title and abstract and, if applicable, by the full text, using the stated inclusion and exclusion criteria. Studies included were coded for research method, principal contribution, limitation, relevance to the IAPSF dimensions and implications for portfolio-dependency. Inter-rater reliability was not calculated as screening and coding were conducted by a single reviewer. As the aim of this review was conceptual integration and theory development, and not in-depth evidence aggregation, the review was not conducted in accordance with the PRISMA guidelines.

The literature reviewed used several approaches of methodological application in use-case prioritization models, with varying insights into the use of AI in use-case prioritization models. Empirical studies that are capability-based typically use survey- based measurement models, estimating relations between AI resources and organizational outcomes [7, 18]. Their strength lies in construct clarity: the capability of AI is broken down into resources, skills, coordination

mechanisms, and complementary assets. However, a limitation is that firm-level capability does not necessarily tell you which use case is most important to prioritize. Even a high-capability organization needs a portfolio approach to selecting among fraud detection, demand forecasting, intelligent automation, customer personalization, or decision support.

A second methodological stream is provided by readiness and adoption studies. Interviewing and survey methods pinpoint the factors that allow for the deployment of AI in the organization [8, 9]. These studies are valuable for prioritization because feasibility cannot be reduced to algorithmic accuracy. Use cases must have data, process ownership, operational integration, legal acceptability and managerial sponsorship. A limitation is that readiness studies do not necessarily provide diagnostic guidance for comparing competing use cases. In reality, there are multiple use cases to consider when the resources are limited, and many readiness frameworks use a general definition of readiness.

A third stream is provided by sociotechnical studies and conceptual studies. The studies discussed here explore AI-driven role transformation, shifts in tasks, decision rights, and accountability [10, 11, 13, 14]. They are particularly important for prioritizing use cases which impact frontline workers, customer decisions or regulated decisions. In some cases, a highly accurate predictive use case can be assigned a lower priority because it becomes overly opaque or because it can negatively affect good decision-making. Their limitation is that sociotechnical insights are difficult to operationalize into comparable prioritization metrics. It can be challenging to translate sociotechnical information into metrics that are comparable unless governance, explainability, exposure to stakeholders, and workflow disruption are specifically weighted.

The fourth stream comprises strategic and review-oriented studies. These articles are all related to transformation and competitive advantage [15]–[17] as well as managerial cognition and information systems governance. They are useful for their general explanatory scope. However, they are limited because unless they are tied to measurable outcomes, time frames, and capability-building effects, they can be claimed too broadly. Thus, the use case prioritization strategy calls for a hybrid methodology: Strategic Value Assessment, Feasibility Scoring, Risk-Governance Evaluation, and Portfolio Sequencing. A purposive subset of seven methodologically representative studies is described in Table 2 to help illustrate how the methodological streams correspond to the IAPSF. The table is not exhaustive; the other reviewed studies are qualitatively summarized in Table 1, Table 3 and the thematic discussion.

Table 2: Methodological comparison and author-coded coverage of the IAPSF dimensions

Ref	Method	Strengths	Limitations	Strategic value	Technical feasibility	Organizational readiness	Risk-governance exposure	Portfolio dependency
[7]	Capability measurement and empirical modelling	Converts AI resources into measurable capability dimensions.	Operates mainly at firm level rather than initiative-portfolio level.	3	2	2	0	1
[8]	Qualitative readiness factor identification	Captures implementation prerequisites before investment escalation.	Does not rank competing AI use cases quantitatively.	1	2	3	2	1
[9]	Integrated adoption model	Links acceptance, organizational support, and environmental factors.	Prioritization among alternative AI applications remains implicit.	2	2	3	1	0
[10]	Conceptual diagnostic framework	Adds value destruction and contextual misfit to selection logic.	Lacks longitudinal validation across AI portfolios.	2	1	1	3	0
[11]	Sociotechnical framework development	Connects people, tasks, structure, and technology in implementation.	Provides limited scoring guidance for investment sequencing.	2	1	3	3	1
[16]	Theoretical information	Explains why adaptive AI	Abstract governance	1	2	2	3	1

	systems analysis	requires distinctive management controls.	implications need operational metrics.					
[18]	Competency-performance empirical analysis	Links AI competencies with performance-relevant capability.	Does not isolate marginal value of individual use cases.	3	2	2	1	2

Note: Scores are author-coded indicators of the extent to which each study substantively addresses a dimension: 0 = not addressed, 1 = limited coverage, 2 = moderate coverage, and 3 = strong or central coverage. The scores represent conceptual coverage within the reviewed literature; they do not represent study quality, effect size, empirical performance, or validated initiative-level scores. Portfolio dependency is coded separately because it informs the sequencing stage of the IAPSF rather than constituting a fifth initiative-assessment dimension.

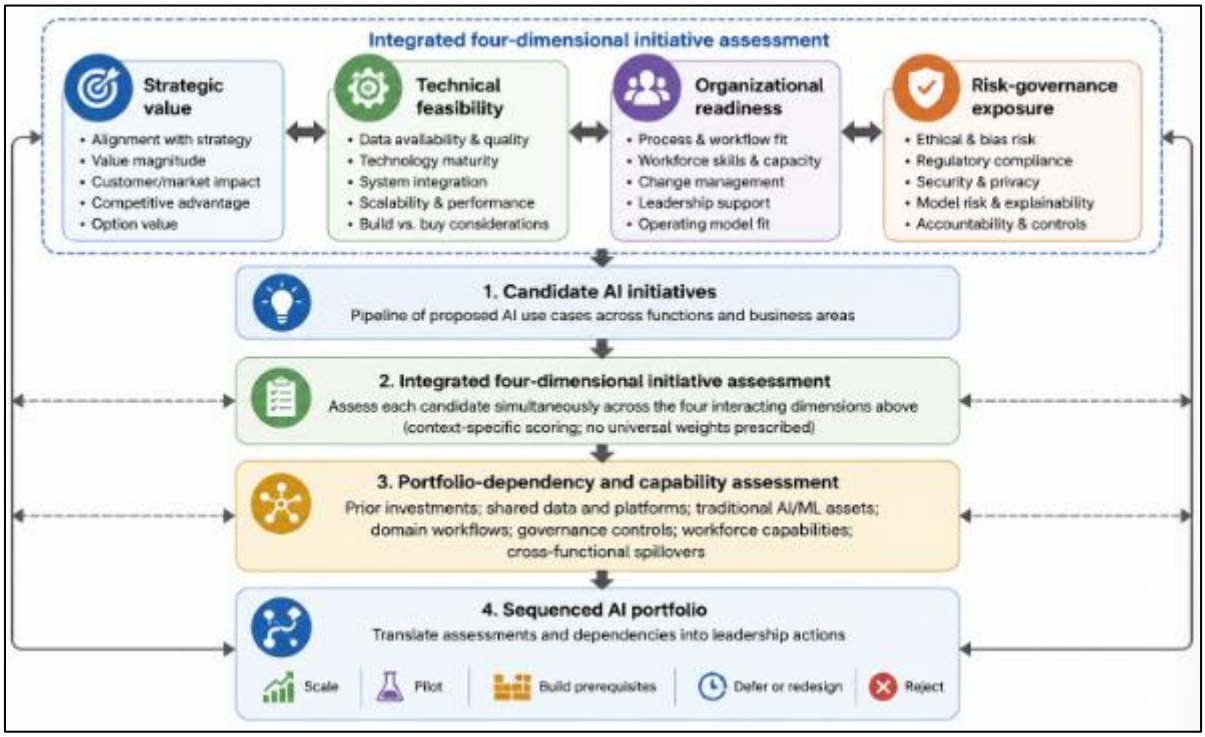


Figure 1: Integrated AI Prioritization and Sequencing Framework (IAPSF): four-dimensional assessment and dependency-aware portfolio sequencing

The review-based IAPSF is summarized in Figure 1. An evidence-informed, initiative-level assessment of capability, readiness, sociotechnical factors, and governance is followed by a portfolio dependency analysis that seeks to identify the following: prerequisite investments, shared assets, capability spillovers, and sequencing constraints [6]–[18]. The dimensions are not additive. In other words, the value of an otherwise promising use case may be reduced by insufficient readiness or significant governance exposure. The literature does not contain validated universal weights, so the framework allows for context-specific ordinal or weighted assessments, assuming that the underlying assumptions are documented. Therefore, its output is not a financial ranking of individual projects, but rather a dependency-aware portfolio decision.

4 DISCUSSION

AI use-case prioritization is best understood as risk-adjusted strategic sequencing, as reported studies indicate. The most consistent theme that can be discerned from the literature is that the focus has shifted from technology selection to the assessment of capability-contingent value. Research on AI transformation and AI capability also indicates that performance impacts are contingent on other factors, such as managerial routines, proficient workers, digital infrastructure, and organizational learning [6, 7]. This distinction is important because candidate initiatives may be favored on the basis of technical novelty rather than organizational value and implementation fit. The literature also suggests that the most successful applications in the early stages are not necessarily the most sophisticated algorithmic

applications. Strong candidates are those that have sufficiently developed value pathways, access to data, ownership of the process, and capability fit to enable measurable deployment.

Another trend is the use of readiness as a gating condition. AI readiness research identifies key requirements for scaling AI, including data governance, AI strategy, skills availability, and organizational culture [8]. Adoption studies in manufacturing also show that perceived usefulness and perceived compatibility are not enough for adoption when organizational support and implementation support is limited [9]. Prioritization therefore requires assessing both attractiveness and deploy ability. If there is a significant amount of risk to doing the use case because of readiness gaps, but it is not that urgent, then it may be very strategic yet not that urgent. Conversely, automation or a decision support application that is smaller may be worth making an early investment as it creates reusable data pipelines, confidence and governance workflows for future high-impact applications.

Table 3: Results comparison

Ref	System / Context	Metric / Basis of Comparison	Outcome
[6]	AI-based transformation projects	Firm performance and transformation value	Performance contribution was linked to process integration and transformation scope.
[7]	AI capability in organizations	Creativity and firm performance	AI capability showed value through combined technical, human, and intangible resources.
[8]	Organizational AI readiness	Readiness factors for implementation	Strategy, data, skills, culture, infrastructure, and governance formed core prerequisites.
[9]	Manufacturing AI adoption	Adoption drivers and organizational support	Usefulness and compatibility required organizational and environmental reinforcement.
[10]	AI and machine learning applications	Value destruction potential	Misfit among data, context, and stakeholder expectations increased downside exposure.
[11]	Organizational AI implementation	Sociotechnical alignment	Implementation depended on coordinated adjustment of work, people, task, and structure.
[13]	Organizational decision-making	Human–AI complementarity	Value increased when machine prediction complemented contextual human judgment.
[16]	AI management in information systems	Adaptive system governance	AI required distinctive management because system behavior can evolve after deployment.

The third trend concerns "sociotechnical fit". Mistakes in using AI and machine-learning systems can lead to loss of value if the models are not designed in line with the decision context, stakeholders' expectations or organizational processes [10]. According to sociotechnical implementation research, the use of AI requires task, role, authority and coordination changes [11]. Human–AI complementarity studies also suggest that focus should be placed on whether AI is replacing human judgment, supporting rather than replacing experts, or whether AI is taking decision authority away from experts [13]. Such research challenges simplistic prioritization models which assign value largely in terms of cost savings or predictive accuracy. If opacity, contestability, or procedural fairness risks cannot be controlled, then an AI use case in credit scoring, hiring, clinical triage, industrial maintenance, customer service, or any other sector may be of lower priority.

A fourth trend is related to adaptive governance. An important principle in information systems research is that an AI system is not a mere object. Learning systems can be modified, produce unforeseen results, and present new accountability issues [16]. Research on learning algorithms in organizations reveals that control and sensemaking are affected by opacity and constant adaptation [14]. This has implications for prioritization as governance cost is not an add-on. It is a component of the overall cost and risk aspects of the use case. For the person making the comparison between two use cases, one question is whether it can be built; another is whether it can be to monitor it, explain it, audit it, update it, and suspend it without hurting the organization.

Collectively, the studies do not provide compelling evidence for a universal ranking model, but for prioritizing on several criteria. Different candidate initiatives can score well on one IAPSF dimension and poorly on another: a candidate initiative that performs well for customer personalization might have high exposure to privacy and explainability while having high revenue potential; a candidate initiative that is easier to implement might have high exposure to privacy

and explainability risks but have lower revenue potential. Figure 2 categorizes the studies summarized in Table 1, using the multidimensional coding in Table 2 and the dominant prioritization lens of those studies [6]–[18].

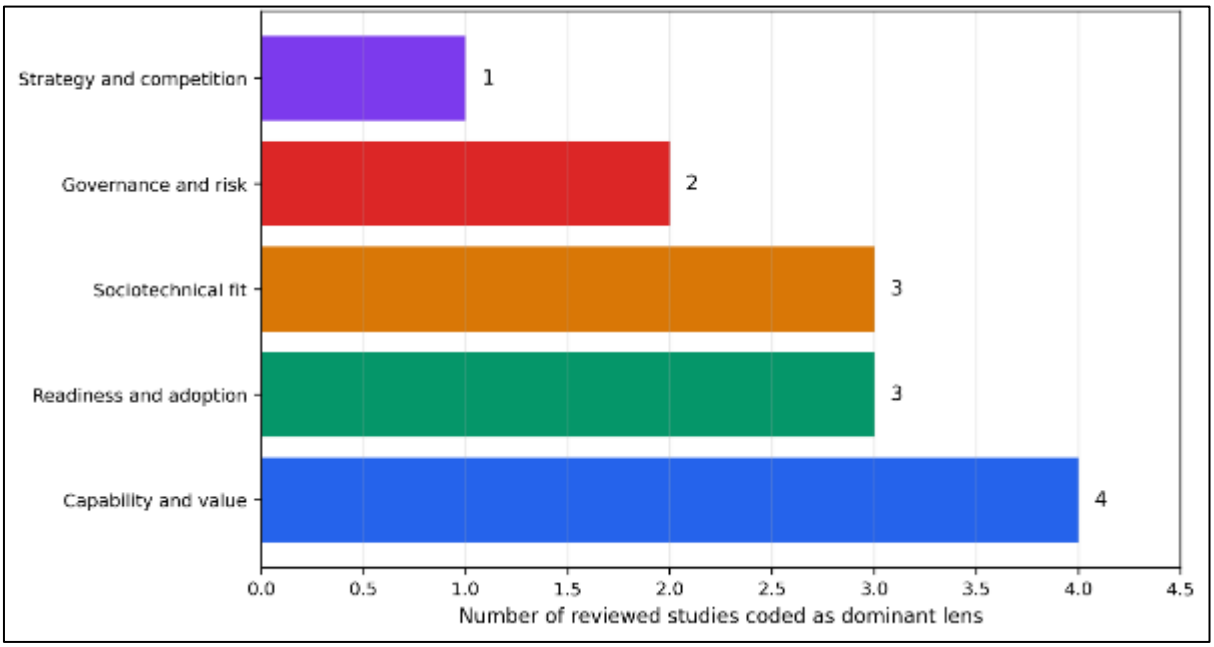


Figure 2: Distribution of prioritization lenses across reviewed studies

As can be seen in Figure 2, capability and value are the most prevalent topics in the literature reviewed and governance and risk are treated less directly. The need to assess governance and risk has become increasingly important due to accountability restrictions on AI prioritization decisions, both in the regulatory and ethical spheres as well as in operations. At an advanced level, a mature model should be able to measure risk and governance, instead of just recommending it.

The comparative results also show some differences. Value-oriented research focuses on the contribution to performance and accumulation of capabilities [6] and [7] and value-destruction and sociotechnical research warn of harm caused by contextual misfits [10] and [11]. This is not a straightforward conflict. It exhibits a range of units of analysis. The sociotechnical and the capability studies tend to concentrate on work-system consequences of implementation and on the capacity of an organization respectively. The contradiction is that the more capable an organization becomes with regard to AI, the more it can do, but each application of AI will require a local fit with organizational processes, accountability and impact on the stakeholders.

The other contradiction is on automation. In some situations, AI can be suitable to reduce labor input and enhance productivity [2, 13], whereas in other scenarios, AI is viewed as a tool to support and supplement human work. This may result in prioritizing substitution projects as high priority in prioritization models based on automation intensity which are effectively characterized as high risk projects. There is a more nuanced distinction among automating routine judgment, augmenting expert decision-making and making new strategic capabilities possible, as suggested by the literature. When the tasks are not changing rapidly, the outcomes are measurable, and the costs of failure are low, automation-heavy use cases may be preferable. In some cases, the augmentation-oriented use cases might be the more suitable ones, when uncertainty, reliance on tacit knowledge, and accountability requirements are high. Figure 3 illustrates a comparison between some of the classes of illustrative AI use cases from the perspectives of strategic value and implementation feasibility. Based on findings concerning value, readiness, sociotechnical factors, and governance in the literature [6]–[18] conceptual coding was done based on the size of the markers.

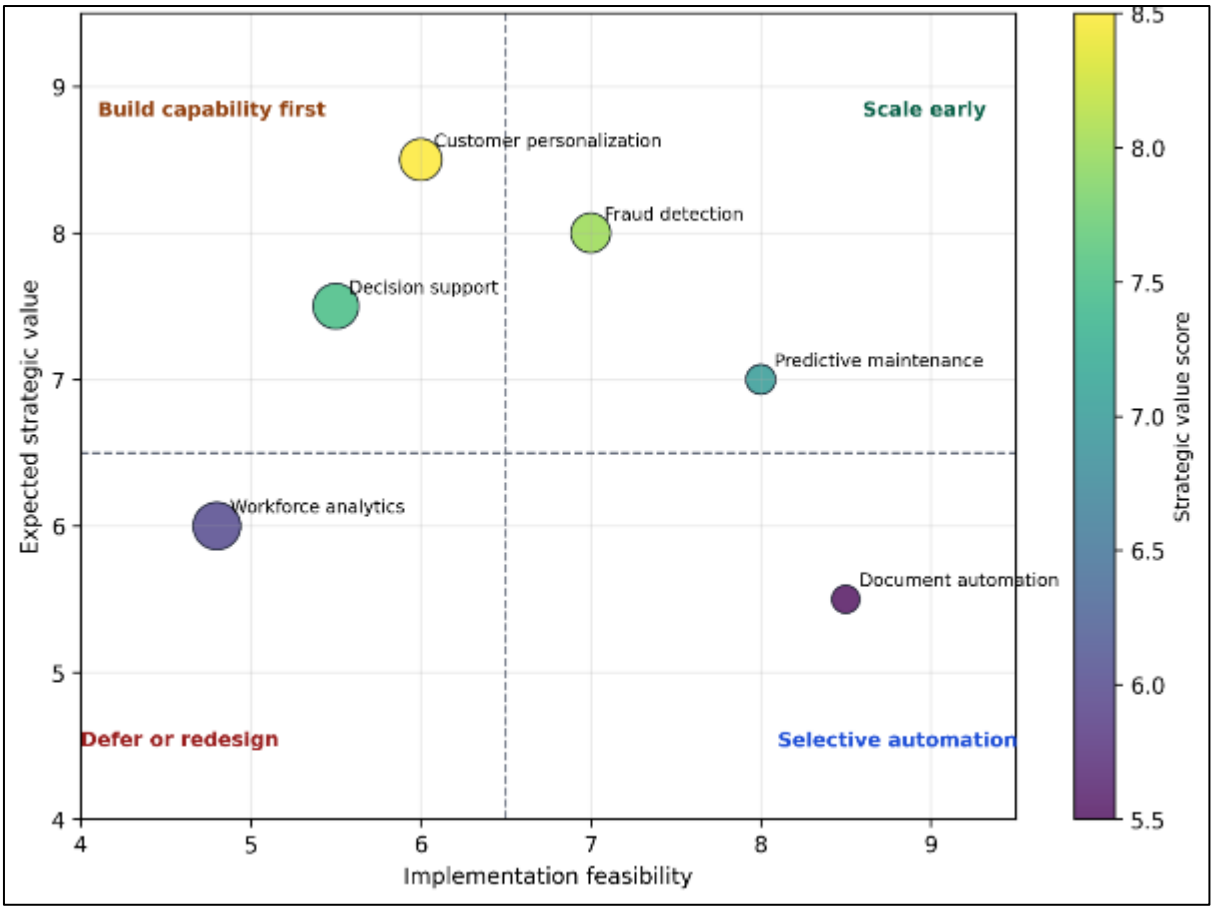


Figure 3: Comparative priority matrix for AI use-case classes

Figure 3 shows that initiative priority depends on the combined IAPSF assessment rather than on value or feasibility alone. It supports differentiated actions such as scaling, capability building, selective automation, or redesign.

Portfolio sequencing constitutes the second stage of the IAPSF. After candidate initiatives have been assessed across the four dimensions, leaders should map prerequisite relationships, shared assets, and spillover effects across the portfolio. In large enterprises, a use case may inherit feasibility and value from earlier investments in data infrastructure, traditional AI and machine-learning models, domain workflows, workforce expertise, and governance controls. Conversely, an early initiative may deserve priority because it creates reusable capabilities for later initiatives. For example, established fraud analytics may provide curated transaction data, monitoring routines, investigation workflows, and model-risk controls that improve the prospects of subsequent generative AI applications in fraud and adjacent customer-service processes. The sequencing decision should therefore consider both the stand-alone priority of an initiative and its dependency-adjusted portfolio contribution. Figure 4 translates this logic into differentiated leadership actions: scale, pilot, build prerequisite capabilities, defer or redesign, or reject.

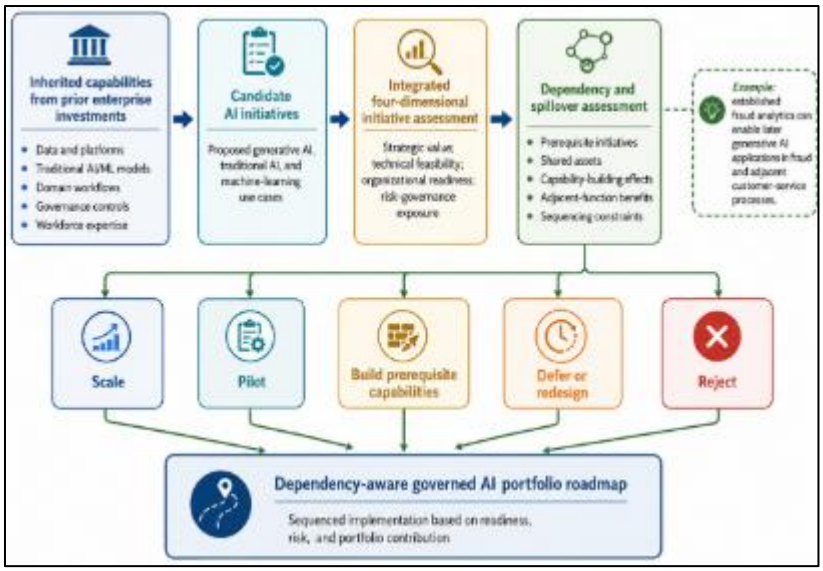


Figure 4: IAPSF dependency-aware portfolio sequencing model for AI initiatives

Figure 4 transforms initiative assessment into a dependency-aware portfolio roadmap. Proposed projects are judged in terms of their use of existing skills and competencies from previous projects and their potential to generate new skills and competencies for future projects. In large organizations, where the number of use cases is often large, sharing of data infrastructure, legacy AI/ML models, domain knowledge, workflow integration, governance teams and monitoring controls is not uncommon. The roadmap therefore categorizes initiatives in different ways: it separates those that are suitable for scaling up from those that need to be piloted and others that need to be redesigned, as well as those that should be avoided. The review identifies four principal measurement gaps: the absence of validated weighting schemes, limited measures of capability spillovers, weak operationalization of governance burden, and insufficient longitudinal evidence concerning portfolio outcomes.

In the business and technology arena, the takeaway is that AI prioritization models must not be a copy of traditional IT backlog prioritization. A good model should contain a value score, feasibility score, readiness score, governance-risk score and portfolio contribution score. It should also differentiate between strategic learning priority and immediate deployment priority. A use case can justify investment even if it is not the most lucrative option, but rather a way to create infrastructure that can be reused, trust relationships within the organization are developed, domain data assets are created, or governance capability is enhanced. On the other hand, a high-value use case might need to be deferred until risk controls are viable, explainability is possible, and process redesign is achievable.

Future Directions

Future studies on the use case prioritization models should focus on measurement, portfolio analysis, and longitudinal research designs. First, there is a need to develop validated scoring instruments that capture the IAPSF dimensions and portfolio interdependence. Although the existing literature offers strong constructs for capability, readiness, adoption, and sociotechnical fit [7, 8, 11, 16] the relationships among these constructs are weak in comparative prioritization models. Empirical research is needed to determine whether multi-criteria prioritization leads to better results in implementing AI than financial-return-only and technology-readiness-only approaches.

A second priority is related to longitudinal evidence. The current research studies tend to focus on one snapshot in time, examining either AI capabilities or their adoption or implementation. The problem with AI prioritization, however, is that it is a sequential process. Early use cases can result in reusable assets like curated data pipelines, monitoring work routines, governance committees, knowledge of workflow redesign, and development of organizational trust. Initial AI use-case decisions should be evaluated in terms of subsequent portfolio performance, success and failure avoidance, and subsequent capability building. This would shift the research in AI capability from possessing resources to developing and managing portfolios of capabilities over time [6, 18].

The third priority is the measurement of risk-adjusted value. Value destruction research and sociotechnical studies demonstrate that AI can create downside exposure in the form of opacity, unfairness, lack of contextual fit, or lack of accountability [10, 14]. These concerns should be turned into prioritization variables that can be measured and used in future models. Potential measures include decision criticality, contestability, intensity of human oversight, explainability requirement, data sensitivity, model drift exposure, and stakeholder harm potential. Governance burden should influence investment sequencing and not appear after investment selection.

Interdisciplinary model testing is the fourth priority. Strategic management can help to determine competitive importance and option value. The concepts of capability, architecture, and governance can be operationalized in information systems research. Multi-criteria decision models can be developed using operations research methods. Work redesign and shifts in authority can be evaluated using organizational studies. Legal/ethical scholarship can help sharpen accountability and harm-evaluation criteria. For the future, it will be important to test AI prioritization models across different industries and sectors, from manufacturing, finance, healthcare and logistics to public administration and beyond, where value, viability, and risk can all have a high degree of variance.

The last factor is transparency of decision tools. Many organizations use proprietary prioritization templates that are not accessible to researchers. Further peer-reviewed research is needed to understand actual practices in prioritization processes, scoring frameworks, steering committees, and post-implementation review processes. Such research would enable comparisons between models and decision outcomes and make the decision tools academically sound and useful to executives.

5 CONCLUSION

AI use-case prioritization remains an emerging research field and not a defined model family. Nevertheless, the reviewed literature offers complementary constructs from the perspective of AI value, capability, readiness, adoption, sociotechnical implementation, governance and strategic management. Integrated within the IAPSF, these constructs suggest that prioritization should focus not only on the financial return of an initiative or technical feasibility, but also on the dependency-adjusted contribution of an initiative to the portfolio.

The IAPSF is conceptually integrative and review-derived but has not yet been empirically validated nor have universal weights been established for its dimensions. Its dimensions, sequencing logic and measures of risk-adjusted value should be tested for future studies across industries and over time. This evidence is essential to support the potential of dependency-aware prioritization to achieve better implementation outcomes and facilitate responsible AI transformation.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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