Quantitative Finance and Economics

QFE, 10(4): 697–727.
DOI: 10.3934/QFE.2026027
Received: 09 January 2026
Revised: 25 August 2026
Accepted: 09 September 2026
Published: 03 November 2026

https://www.aimspress.com/journal/QFE

Research article

Artificial intelligence's networking scalability: ESG value creation and bankability issues

Roberto Moro-Visconti[1,*], Salvador Cruz Rambaud[2] and Joaquín López Pascual[3]

[1] Department of Economics and Business Management Sciences, Università Cattolica del Sacro Cuore, Milan, 20123, Italy
[2] Department of Economics and Business, Universidad de Almería, Almería, 04120, Spain
[3] Department of Business Economics, Universidad Rey Juan Carlos, Madrid, 28032, Spain

* **Correspondence:** Email: roberto.morovisconti@morovisconti.it; Tel: +39-02-72341.

Abstract: Artificial intelligence (AI) improves organizational performance, yet the financial mechanisms through which these gains become financeable cash flows remain insufficiently specified. While research emphasizes productivity and innovation, lenders focus on profitability, cash generation, debt-service capacity, leverage, liquidity, and covenant compliance. In this paper, we developed a finance-oriented framework linking AI-enabled organizational coordination to lender-oriented financial indicators. Using a transparent explanatory simulation anchored to a reference business plan, we modeled how AI capability, organizational readiness, coordination, implementation timing, and financial absorptive capacity translated into revenues, operating costs, EBITDA, operating cash flow, cash available for debt service, debt-service coverage, and leverage. The framework separated AI operating effects from ESG considerations and provided an auditable basis for scenario analysis, lender communication, and future empirical calibration. Its central implication was that AI-related operating gains create financing value only when they are sufficiently credible, persistent, and timely to survive the implementation trough and preserve debt-service capacity.

Keywords: artificial intelligence; organizational coordination; digital transformation; bankability; financial resilience; scenario analysis; multilayer networks; ESG governance

JEL Codes: C63, G31, G38, M21, O33

Highlights:

- Transmission mechanism: AI-linked operational changes affect bankability through accounting translation, cash conversion, and the preservation of lender capacity.
- Complementarity: ESG-aligned governance can affect the credibility, persistence, and risk profile of AI-related benefits and, where supported by evidence, financing conditions.
- Method: A transparent with-or-without scenario simulation translates explicit operational assumptions into credit-relevant indicators without presenting them as causal estimates or forecasts.

1. Introduction

Artificial intelligence (AI) has evolved from a set of specialized computational techniques into a general-purpose organizational technology that can reshape decision-making, information flows, and resource allocation. Advances in machine learning, generative AI, large language models, and autonomous decision-support systems have expanded the range of activities that can be automated or augmented. As firms move from experimentation to implementation, the central economic question is no longer whether AI can perform particular tasks, but whether organizations can convert those capabilities into durable operating and financial outcomes.

Research has documented potential benefits associated with AI, including higher productivity, improved forecasting, faster decisions, stronger customer engagement, supply-chain coordination, innovation capability, and strategic responsiveness (Enholm et al., 2022; Mishra et al., 2022; Lui et al., 2022). These contributions have advanced understanding of AI-enabled performance. However, much of the literature evaluates AI through operational or strategic indicators, while considerably less attention is given to the metrics used by lenders, credit analysts, and corporate finance practitioners.

This distinction is economically important. A firm may improve forecasting accuracy or process speed without generating an equivalent improvement in profitability, liquidity, or debt-service capacity. Implementation expenditure, parallel-system costs, working-capital absorption, or delayed adoption may offset revenue growth. Conversely, modest operational improvements may materially strengthen financial resilience when they quickly convert into cash and debt-service capacity. The value of AI depends not only on technical capability, but also on the organizational and accounting mechanisms through which that capability becomes financially visible.

Credit institutions and investors do not normally finance AI in the abstract. They assess EBITDA, operating cash flow, free cash flow available for debt service (FCADS), debt-service coverage ratio (DSCR), leverage, liquidity, and covenant compliance. Bankability consequently requires a disciplined bridge from operational claims to financial statements. A credible model must show which process changes affect revenue or cost, when implementation expenditure occurs, how cash conversion evolves, and whether the resulting financial profile remains sustainable in the trough year, not just on average.

The organizational nature of implementation adds a second challenge. AI rarely creates value through isolated technological deployment. Successful adoption usually requires complementary investments in data governance, managerial capability, workforce skills, process redesign, cybersecurity, accountability, and organizational learning. Two firms using similar technologies may obtain very different outcomes. The economically relevant construct is realized organizational capability, not the mere presence of an AI system.

This observation motivates a coordination-based perspective. Firms operate through interacting networks of employees, management teams, customers, suppliers, lenders, regulators, and technology providers. AI can reduce information latency, error rates, verification costs, and coordination frictions across these relationships. Network analysis is useful because it represents where interactions occur and where bottlenecks arise. Nevertheless, network topology does not create financial value on its own. Financial value arises only when better coordination changes business operations and those changes propagate through accounting identities into cash generation and financing capacity.

A further source of ambiguity concerns environmental, social, and governance (ESG) factors. AI and ESG are increasingly considered together, although their financial effects arise through partly distinct channels. AI can directly affect operations, information processing, coordination, and decision quality, whereas ESG-related governance primarily influences the credibility, accountability, persistence, and risk profile of those benefits. It may also affect disclosure quality, stakeholder confidence, risk controls, and, where supported by observable evidence, financing conditions (Sætra, 2023; Kar et al., 2022). Treating these effects as a single source of value risks conceptual ambiguity and double counting. The framework therefore separates AI-enabled operating effects, organizational realization, and ESG-related governance and financing effects, while enabling their interactions to influence the ultimate financial outcome.

Against this background, the research question is: Under what operating, organizational, ESG-governance, and financing conditions can AI-enabled coordination improve cash generation and bankability, and when can implementation weaken lenders' debt-service capacity?

This formulation treats bankability as the outcome of several interacting conditions rather than as the automatic financial consequence of AI adoption. Operating improvements must first be organizationally realized, converted into cash, and sustained through the implementation period. ESG-related governance can reinforce this process by improving accountability, transparency, risk control, and the credibility of projected benefits. However, it should not be assumed to generate an independent financing advantage unless that effect can be documented. The relevant question is therefore not only whether AI-related benefits emerge, but whether they are sufficiently credible, persistent, and timely for the firm to finance the path required to reach them.

We adopt an explanatory simulation rather than a causal empirical design. We neither estimate an average treatment effect of AI adoption nor present the numerical scenarios as forecasts. Instead, we develop a transparent financial propagation framework in which outcomes depend on explicit assumptions about operating performance, organizational readiness, implementation frictions, ESG governance, and financing constraints. This is not merely a residual methodological choice. Firms and lenders must assess forward-looking transformation programs before project-specific longitudinal evidence becomes available. The framework therefore makes that prospective assessment explicit, traceable, financially reconciled, and stress-testable, rather than substituting scenario analysis for causal inference.

The paper makes four contributions. First, we reframe AI as an organizational financial capability rather than a technology expenditure. Second, we identify effective coordination as the organizational transmission mechanism and accounting as the translation mechanism through which operational changes become cash-flow consequences. Third, we treat bankability as a dynamic question of financial absorptive capacity, implementation troughs, and lender capacity rather than as a simple function of expected EBITDA. Fourth, we separate AI operating effects, organizational realization, and ESG-related financing credibility to avoid double counting.

The remainder of the paper proceeds as follows. In Section 2, we review and position the relevant literature. In Section 3, we develop the conceptual framework. In Section 4, we explain the methodology. In Section 5, we present the numerical illustration. In Section 6, we discuss the theoretical and practical implications, limitations, and directions for future research, and in Section 7, we conclude the study.

2. Literature review and conceptual positioning

The literature relevant to AI and corporate finance has grown rapidly, but it remains segmented. One stream asks whether AI improves firm performance; another examines the organizational capabilities required to obtain those gains; network research explains how connected systems behave; sustainability studies consider the environmental and governance consequences of digital technologies; and valuation research asks how such effects should enter financial estimates. These conversations increasingly overlap, but they rarely follow the same economic effect from AI capability to organizational change, accounting outcomes, cash generation, and lender-relevant financial capacity.

That missing connection matters for the research question we develop. The issue is no longer simply whether AI can create value; substantial evidence and conceptual work suggest it can. The more difficult question is when AI-enabled organizational coordination becomes financially observable and sufficiently credible, timely, and resilient to improve bankability. Answering this requires bringing together literature that normally stops at different points along that path.

2.1. From AI adoption to value realization

Research on AI and firm performance has moved beyond the early assumption that technology investment should translate directly into productivity or value. Enholm et al. (2022), in their review of AI and business value, showed that value realization depends on complementary organizational resources and capabilities. Mishra et al. (2022) similarly connected a firm's strategic focus on AI with performance, while Lui et al. (2022) examined the relationship between AI investment and firm value. Taken together, this literature suggests a useful distinction: AI investment is observable, but AI value is conditional.

That distinction becomes even more important with generative AI. GenAI lowers the cost of producing, recombining, and interpreting information, but its organizational effects depend on how it enters existing processes. Cano-Marin (2024) showed how generative AI is reshaping innovation-related information and business applications. Dwivedi and Al-Banna (2025) extended the discussion toward sustainability, highlighting the opportunities created by GenAI and the tensions surrounding its responsible deployment. Pérez-García (2025), in the more specific context of predictive maintenance, illustrated how agentic AI and retrieval-augmented generation can be embedded in an operating process rather than treated simply as general-purpose technologies.

The broader digital-transformation literature points in the same direction. Acciarini et al. (2023) showed that big data can support business-model innovation. However, the relationship depends on the organizational capacity to turn information into changes in how value is created and captured. Wang, Gao, and Zhang (2025) placed data-driven decision-making and digital leadership closer to the center of this conversion process, associating them with creativity and

sustainable competitive advantage. These studies help move the argument from technology possessed to technology organizationally used.

This is an important boundary for this study. AI expenditure, installed models, patents, or user adoption may indicate technological commitment. However, none alone shows that a firm has changed the processes through which revenue, costs, working capital, or risk are generated. Moro-Visconti et al. (2023) made the financial implications more explicit by connecting AI-driven scalability to sustainability and firm valuation. Nevertheless, scalability and valuation leave an intermediate question open: Through which organizational mechanisms do expected AI benefits become cash flows that a lender can recognize?

The literature therefore provides considerable evidence around the beginning and end of the value chain, but less integration across the middle. In this paper, we locate our contribution in that middle: the transmission from AI capability through organizational coordination and readiness to accounting and cash-flow consequences.

2.2. Coordination, networks, and the organizational layer

Network theory provides a natural language for this problem because organizations are not collections of isolated AI use cases. They are systems of interdependent relationships among functions, managers, employees, suppliers, customers, platforms, and information sources.

The foundational work of Barabási and Albert (1999) demonstrated that many real networks do not evolve as homogeneous random structures; connectivity becomes concentrated, and particular nodes acquire disproportionate importance. Barabási (2016) developed this insight into a broader account of network structure, robustness, and diffusion. Bianconi (2018) extended the analysis to multilayer networks, where the same actors can be connected through different kinds of relationships. This is particularly relevant for firms, where information, operational, contractual, technological, and financial links coexist rather than form a single network.

For AI-enabled organizations, the implication is not that more connections are necessarily better. A new informational link can reduce latency or improve visibility, but it can also duplicate information, create cyber exposure, increase verification requirements, or blur accountability. What matters is effective coordination: Whether the relevant organizational nodes can exchange and act on information with sufficient speed, reliability, and clarity to improve an economically meaningful process.

This interpretation gives network measures a more precise role in this framework. Density, centrality, or reachability are not treated as financial variables. They help identify where coordination may improve or deteriorate. Financial relevance begins only when the network change affects an operating mechanism; for example, forecast accuracy, order processing, exception handling, inventory management, reconciliation effort, or supplier coordination.

The distinction is subtle but important. It prevents us from claiming that network topology creates value. Instead, network structure provides the organizational layer through which technical AI capability may become operationally consequential. This also explains why the same AI architecture can generate different outcomes across firms: It enters different networks, with different bottlenecks, decision rights, and capacities to absorb change.

2.3. Readiness, leadership, acceptance, and resilience

Technology does not coordinate an organization on its own. Someone must trust its outputs, decide how they enter workflows, determine who remains accountable, and redesign routines when the technology changes how information flows. This makes organizational readiness more than a convenient coefficient in a model.

Wang, Gao, and Zhang (2025) are especially relevant here because they connected digital leadership and data-driven decision-making with organizational outcomes. Their findings support the idea that managerial and decision-making capabilities must mediate the effect of technical capability. For this study, the implication is that readiness should not be understood simply as employee willingness to use AI; it encompasses the organization's ability to convert AI-generated information into repeatable decisions.

Acceptance nevertheless matters. Medina-Molina et al. (2025) showed that ethical considerations influence young people's interest in using AI. Although their setting is not corporate lending, the underlying insight is transferable with appropriate caution: Adoption is partly behavioral and normative. A technically effective tool that users distrust, avoid, or perceive as ethically problematic may produce less organizational realization than its technical characteristics suggest.

Related evidence on information behavior reinforces that point. Gallego Gómez et al. (2024), examining Generation Z's use of social networks as information platforms, illustrated how trust, habits, and user characteristics condition the use of digital information channels. Such findings do not directly establish enterprise AI readiness, but they warn against treating information availability and information use as equivalent. In an organizational setting, the same distinction applies between an AI recommendation being generated and that recommendation becoming part of an accountable decision.

Resilience adds a temporal dimension. Wang and Zhang (2026) connected AI-supported information capabilities with strategic adaptation and entrepreneurial success. This shifts attention from whether AI generates an initial benefit to whether the organization can preserve or reconfigure that benefit as conditions change. Supplier failures, model drift, cyber incidents, staff turnover, and regulatory changes can interrupt the path between installed capability and financial outcome.

Readiness and resilience therefore perform different functions in the proposed architecture. Readiness affects realization; resilience affects persistence, and neither should be interpreted as a generic multiplier that makes AI valuable. Both describe organizational conditions that influence whether an initially plausible technical benefit survives long enough, and at sufficient scale, to become financially observable.

2.4. ESG, governance, and the credibility of AI-related benefits

The sustainability literature introduces a second distinction that is central to the paper: between creating an operating benefit and making that benefit credible to capital providers.

Kar et al. (2022) showed that the relationship between AI and sustainability spans environmental, social, and economic dimensions and is neither uniformly positive nor automatic. Sætra (2023) made this tension explicit through the AI ESG protocol, emphasizing the need to identify and disclose the environmental, social, and governance implications of AI capabilities, assets, and activities. Dwivedi and Al-Banna (2025) reached a similar position from the perspective of GenAI, where sustainability opportunities coexist with governance, resource, and ethical concerns.

This literature is important because it prevents ESG from being inserted into valuation as an unexplained premium. AI may reduce waste, improve resource allocation, or strengthen monitoring, but it can simultaneously increase energy consumption, cyber exposure, data-governance costs, or the need for human oversight. The financial effect is therefore conditional on the specific channel.

Governance is also endogenous. Ferreira et al. (2025) showed that the relationship between CEO career horizon and ESG performance varies with power distance. This is particularly useful for the present argument because it connects governance outcomes to managerial incentives and cultural context. Governance quality cannot simply be inferred from the existence of policies or committees; incentives and organizational context affect how those mechanisms operate.

For lenders, this moves ESG closer to credibility and downside control than to an automatic operating uplift. Traceability, clear decision rights, assurance, cybersecurity, and transparent reporting can make projected AI benefits easier to verify. Conversely, weak controls may make even attractive operating forecasts difficult to incorporate into a credit case.

Wang and Zhang (2025) provided a complementary perspective by linking AI-enabled supply chains, innovation, collaboration, and proactive sustainability strategy to ESG performance in the energy industry. Their work illustrates that AI, interorganizational coordination, and sustainability can interact rather than operate as separate domains. Nevertheless, the financing consequence still requires an additional translation: Better ESG performance matters for bankability only insofar as it changes expected cash flows, downside exposure, information asymmetry, or financing terms.

This framework therefore deliberately separates the operating channel from the governance channel. The former may change revenue, recurring costs, or working capital. The latter primarily changes the reliability, risk, and finance-readability of those expectations. This separation reduces the risk of double counting and makes explicit where empirical evidence is required before a governance benefit can be incorporated into financing assumptions.

2.5. From operating effects to valuation and bankability

Researchers have also examined the endpoint of the transmission process: valuation and financing. Here, too, the central problem is not the absence of useful approaches but the distance between them and the organizational mechanisms described above.

Inard (2023) examined how ESG considerations can enter cash-flow valuation, while Nguyen et al. (2025) considered integrating ESG factors into equity valuation. Both are useful because they force sustainability claims into financial variables rather than leaving them as qualitative overlays. Moro-Visconti et al. (2023) similarly connected AI-enabled scalability with sustainability and the valuation of traditional firms. Collectively, these studies move the discussion toward the financial consequences of technological and ESG transformation.

For this study, however, valuation is not the final criterion. A project can create expected enterprise value and still be difficult to finance. Debt providers care not only about the magnitude of expected cash flows but about their timing, volatility, senior claims, and the liquidity available when downside conditions occur.

This distinction is particularly relevant to capital structure. Feldhütter and Pedersen (2025) examined how ESG-oriented investors can affect capital-structure decisions, showing that sustainability preferences can interact with financing rather than remaining external to it. Choi et al. (2025), using a dynamic Bayesian network to investigate financial variables associated with firm value,

likewise emphasized that financial variables are interdependent rather than isolated. These perspectives align with a central premise of this paper: improvements in operating performance cannot be interpreted independently of leverage, liquidity, debt service, and the firm's initial financial position.

The financing landscape is also changing. Palos-Sánchez et al. (2025) examined neobanks and FinTech from the perspective of sustainable finance and entrepreneurship. Their contribution broadens the relevant set of capital providers and financing technologies. Digitalization may therefore affect bankability in two ways: by changing the operating organization seeking finance and by changing the institutions and channels through which finance is supplied.

This does not make conventional credit analysis obsolete. On the contrary, it makes the translation into lender-readable measures more necessary. Whether finance comes from a traditional bank, a FinTech platform, or another intermediary, projected technological benefits have to confront cash conversion, leverage, liquidity, and repayment capacity.

The missing bridge is therefore from organizational realization to financeability. Existing studies provide important pieces: AI investment and firm value, AI scalability, ESG valuation, sustainable capital structure, and technology-enabled finance. However, they do not provide an integrated mechanism showing how changes in organizational coordination pass through accounting lines into FCADS, DSCR, and covenant compliance, particularly when implementation costs precede benefits.

2.6. Research gaps and propositions

The literature can now be read as a sequence rather than a collection of themes. Table 1 summarizes that sequence and, importantly, shows where this study enters it.

Table 1. Literature strands, main references, and remaining issues.

Literature strand	What prior research establishes	Main references	Remaining issue for this study
AI and business value	AI can affect performance and firm value, but realization depends on complementary capabilities.	Enholm et al. (2022); Lui et al. (2022); Mishra et al. (2022); Moro-Visconti et al. (2023)	How does technical potential travel through the organization into lender-visible cash flow?
GenAI and process innovation	GenAI and data-intensive technologies can alter innovation, information processing, and specific operating processes.	Acciarini et al. (2023); Cano-Marin (2024); Dwivedi & Al-Banna (2025); Pérez-García (2025)	How can process change be distinguished from technology adoption and linked to financial outcomes?
Networks and coordination	Organizational outcomes depend on connectivity patterns, centrality, multilayer relationships, and effective information flows.	Barabási & Albert (1999); Barabási (2016); Bianconi (2018)	Which network changes matter economically, rather than topologically?
Organizational realization	Leadership, decision routines, user acceptance, and resilience condition whether digital capability is used and sustained.	Gallego Gómez et al. (2024); Medina-Molina et al. (2025); Wang, Gao, & Zhang (2025); Wang & Zhang (2026)	How should readiness and resilience enter the transmission from AI capability to cash flow?

Continued on next page

Literature strand	What prior research establishes	Main references	Remaining issue for this study
AI, ESG, and governance	AI can affect sustainability, while governance, incentives, and context shape the credibility and risk of those effects.	Ferreira et al. (2025); Kar et al. (2022); Sætra (2023); Wang & Zhang (2025)	How can operating effects be separated from governance and financing effects without double counting?
Valuation and financing	ESG, AI scalability, and interconnected financial variables can affect valuation and financing decisions.	Choi et al. (2025); Feldhütter & Pedersen (2025); Inard (2023); Moro-Visconti et al. (2023); Nguyen et al. (2025)	When does expected value creation become debt-service capacity?
Technology-enabled finance	Digital financial intermediaries broaden financing channels and change interactions with borrowers and users.	Palos-Sánchez et al. (2025)	Does a changing lender landscape alter the evidence required to establish bankability?

The gap revealed by this comparison is narrower, and more defensible, than a claim that researchers have overlooked the financial value of AI. The missing element is an auditable transmission architecture connecting bodies of literature that usually examine different stages of value realization. AI research is strongest on capability, adoption, and performance; organizational research explains important complements; network science provides a structural account of coordination; ESG research adds governance and sustainability; and valuation and finance research translate selected effects into financial outcomes. What remains weakly integrated is the path connecting them.

This distinction underlies the research question set out in Section 1: Under what operating, organizational, ESG-governance, and financing conditions can AI-enabled coordination improve cash generation and bankability, and when can implementation weaken lenders' debt-service capacity?

Research offers substantial evidence on AI capabilities, organizational complements, network relationships, ESG practices, and firm performance. What remains less developed is the connection between these elements and the financial criteria lenders use to assess firms. In particular, the literature provides limited guidance on how improvements in organizational coordination should flow from the operating level to revenue and cost, from accounting performance to cash generation, and from cash generation to debt-service capacity. The gap is therefore not the absence of evidence that AI can affect firms, but the absence of an integrated and auditable organizational-to-finance transmission mechanism.

The framework developed here addresses this gap through five related propositions. They do not represent five independent effects. Rather, they describe successive conditions along the same transmission path: Coordination creates operating potential; organizational capabilities determine how much of that potential is realized; resilience and timing shape its persistence; governance affects its credibility and risk profile; and the firm's existing financial position ultimately determines whether the resulting cash-flow path is bankable. Because the numerical analysis is an explanatory simulation rather than a causal empirical test, the propositions also differ in the extent to which they can be examined in this study.

Effective coordination is the first link in this chain. AI can improve the speed and quality of information flows across functions, customers, suppliers, and other organizational interfaces. Lower decision latency, fewer errors and exceptions, and reduced verification effort can support faster revenue

conversion or lower recurring costs. However, these improvements are not automatic consequences of greater connectivity. They depend on whether the organization can incorporate AI-enabled information into actual routines and decisions. A technically capable system operating within poorly designed processes, weak data structures, or unclear responsibilities may generate little economic benefit. Coordination potential must therefore be filtered through organizational readiness and implementation quality before it can affect operating performance.

P1. Improvements in effective coordination can support revenue conversion and operating-cost efficiency, but the magnitude realized depends on organizational readiness and implementation quality.

The simulation illustrates the financial consequences associated with the operating channels described in P1, but it does not causally establish that AI-enabled coordination produces the assumed revenue or cost changes. Those links remain calibration relationships to be estimated with firm- or process-level data.

Organizational readiness, however, is not simply a generic implementation condition. Leadership and the quality of data-driven decision-making influence whether technical outputs are acted upon, whether decision rights are adapted, and whether information generated by AI reaches the people and processes able to use it. This distinction matters because formal adoption and effective use are not equivalent. Firms may acquire similar AI capabilities while differing substantially in their ability to embed them in operating decisions. Digital leadership can align technology with business priorities, while data-driven decision routines can turn model outputs into repeatable organizational action. These capabilities therefore sit between technical potential and realized operating performance rather than alongside them.

P2. Digital leadership and data-driven decision-making mediate the conversion of technical AI capability into operating outcomes.

P2 is theoretically represented in the organizational-readiness component of the framework but is not directly evaluated by the present simulation. Testing the proposed mediation requires observable measures of leadership, decision processes, and AI use that are not available in the illustrative financial model.

Realization also has a time dimension. Even where AI improves operations, benefits may emerge gradually and may weaken when implementation encounters disruption. Training requirements, process migration, parallel systems, supplier dependence, cyber incidents, or managerial turnover can delay or interrupt the expected improvement. Strategic resilience therefore matters, not simply because it protects the firm against shocks, but because it influences whether AI-related gains persist long enough to become financially meaningful. Implementation timing has a related effect: Costs may be incurred immediately while revenue gains, cost efficiencies, or working-capital benefits appear only later. Two programs with the same expected steady-state benefit may consequently produce very different cash-flow paths.

P3. Strategic resilience and implementation timing affect the persistence and cash-flow profile of AI-related benefits.

The simulation examines the timing implications of P3 through the implementation-friction scenario and the resulting deterioration in FCADS and DSCR. It does not independently estimate the effect of strategic resilience on the persistence of AI benefits; that component remains to be calibrated empirically.

A different transmission channel applies to ESG-aligned governance. Governance quality does not mechanically increase sales or reduce operating expenditure. Its relevance lies primarily in making

projected benefits more credible and controllable. Traceability, disclosure quality, clear accountability, effective risk controls, and appropriate oversight can reduce information asymmetry and enable lenders to assess whether expected operating improvements are sufficiently robust to enter a financing case. These characteristics may influence required liquidity, covenant structures, perceived risk, or financing terms. Furthermore, responsible governance consumes resources through assurance, cybersecurity, documentation, compliance and human oversight. Treating governance as an automatic EBITDA uplift would therefore obscure its actual role and its cost.

P4. ESG-aligned governance affects bankability primarily through information credibility, downside-risk control and, where supported by evidence, financing conditions, rather than through an automatic increase in EBITDA.

P4 is not empirically tested in the simulation. Consistent with the framework's separation of operating and governance channels, no automatic ESG premium is incorporated into EBITDA, debt pricing, or the cost of capital. The proposition requires empirical evidence linking observable governance characteristics to financing outcomes.

The final step concerns bankability. Operating improvement is relevant to lenders only after considering its timing and cash conversion against the firm's financial commitments. Implementation CapEx, working-capital absorption, and temporary duplication can precede benefits and create a financing trough even when the steady-state investment case is attractive. Whether that trough can be absorbed depends on debt service, minimum liquidity, and the debt-service capacity available before implementation begins. Bankability therefore cannot be inferred from the magnitude of expected EBITDA improvement alone. The same operating program may be readily financeable for a firm entering the transition with strong margins and liquidity, yet create covenant stress for a more highly leveraged or financially constrained borrower.

P5. The contribution of AI-enabled coordination to bankability depends not only on the magnitude of expected operating benefits, but also on their timing relative to implementation expenditure, working-capital absorption, debt service, liquidity buffers, and pre-existing debt-service capacity.

P5 is the proposition most directly examined by the numerical simulation. The scenario and sensitivity analyses show mechanically how implementation friction, cash conversion, and different levels of starting financial capacity alter FCADS, DSCR, leverage, and covenant capacity. These results illustrate the proposed mechanism within the reference financial structure; they should not be interpreted as causal evidence or as estimates of the average financial effect of AI adoption.

Taken together, the five propositions define a sequential argument rather than a claim that AI adoption is inherently value-creating. P1 and P2 concern the realization of operating potential; P3 concerns its timing and persistence; P4 concerns the credibility and risk surrounding that potential; and P5 concerns its conversion into bankability. The framework thus moves the analytical focus from whether a firm has adopted AI to whether AI-enabled organizational change can produce cash flows that are observable, durable, timely, and sufficient to preserve debt-service capacity.

Table 2. Positioning relative to the literature.

Existing emphasis	Proposed framework
AI adoption	AI realization
Technology	Organizational capability
Productivity	Cash generation and debt-service capacity
Network topology	Effective coordination
Strategic value	Financial resilience and bankability
Static association	Sequential propagation
Combined AI/ESG effect	Separate operating and governance channels

3. Conceptual framework

The conceptual framework translates these foundations into a structured organizational to finance pathway linking AI capability, organizational realization, operating performance, cash generation, and bankability.

3.1. The organizational-to-finance transmission problem

AI does not directly create EBITDA, cash flow, or borrowing capacity. It creates technical and informational capabilities whose economic consequences depend on organizational realization. The model decomposes transformation into a sequence of economically interpretable stages.

AI capability defines what the technology could support. Organizational readiness determines how much of that potential can be implemented. Effective coordination identifies whether information and decisions improve across material process links. Operating effects then alter revenue, recurring cost, working capital, and risk. Accounting identities translate those effects into EBITDA and cash. Lender-oriented ratios finally determine whether the resulting profile is bankable.

This sequence is our central organizing idea. It prevents the network layer from being treated as an independent source of value and prevents operating claims from being confused with cash generation.

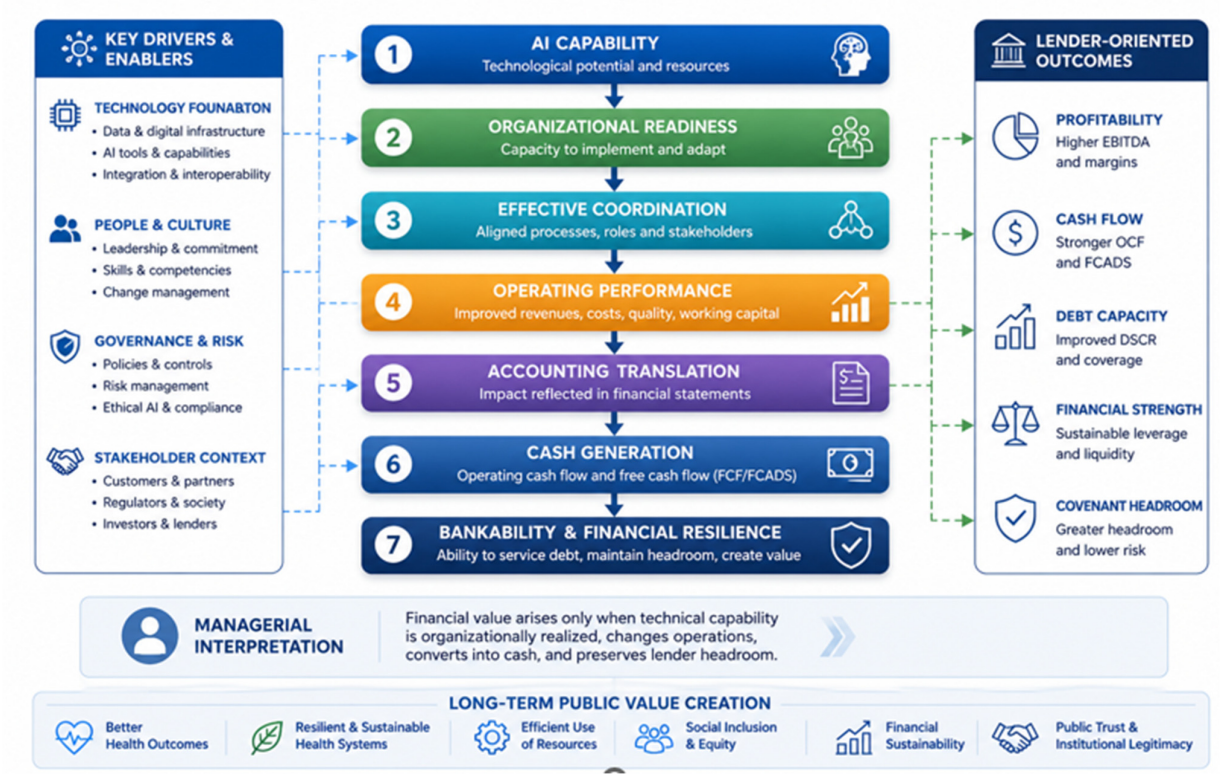


Figure 1. Organizational-to-finance transmission architecture (Source: Authors' conceptualization and prompt; graphical rendering produced using OpenAI).

Managerial interpretation: Financial value arises only when technical capability is organizationally realized, changes operations, converts into cash, and preserves lenders' debt-service capacity.

3.2. Key definitions

Organizational readiness. The firm's capacity to convert technical potential into sustained operating improvements through governance, leadership, workforce preparation, data quality, and implementation effectiveness.

Effective coordination. The quality of information and decision flows across material organizational links, reflected in lower latency, fewer errors, lower verification costs, and clearer accountability and reachability.

Financial resilience. The capacity to maintain liquidity, absorb implementation shocks, and continue meeting contractual obligations under adverse but plausible conditions.

Bankability. The capacity of a business plan or investment program to support sustainable financing on acceptable terms, assessed not as a binary attribute but through cash generation, DSCR, leverage, liquidity, covenant buffers, and the ability to withstand temporary implementation stress.

Financial absorptive capacity. The pre-existing liquidity, covenant buffers, and debt-service capacity available to absorb the temporary cash-flow deterioration that may arise before AI-related operating benefits are realized.

3.3. Accounting as the translation mechanism

Accounting is not a reporting afterthought in this framework; it is the mechanism that disciplines the translation from organizational claims to finance. Better inventory forecasting, for example, is financially relevant only when it reduces inventory or stockouts, changes working capital or revenue, and thereby affects cash available for debt service.

Using accounting identities provides traceability. Every change in EBITDA must originate from a revenue or operating-cost assumption. Every change in FCADS must be reconciled to EBITDA, capital expenditure, working capital, taxes, and other specified deductions. Every change in DSCR must then arise from FCADS or debt service, not from an unexplained technology premium.

Table 3. Illustrative financial transmission chain.

Organizational change	Accounting effect	Financial consequence
Faster and better decisions	Higher conversion or lower leakage	Revenue and EBITDA increase
Improved procurement	Lower recurring operating cost	EBITDA and FCADS increase
Improved inventory forecasting	Lower inventory requirement	Working capital releases cash
Implementation delay	Benefits postponed; temporary duplication	Liquidity and DSCR may weaken
Verified governance and controls	Lower uncertainty or financing friction	Potentially stronger covenant or pricing terms

4. Methodology

The methodology operationalizes this framework through a transparent scenario-based design that traces how changes in coordination and organizational realization propagate through operating assumptions, accounting outcomes, cash flows, and bankability indicators.

4.1. Research design and boundaries

The quantitative component is a bounded with-or-without simulation anchored to a reference business plan. The baseline describes the firm without the incremental AI program considered in the illustration. Alternative scenarios modify specified revenue, operating-cost, implementation-cost, and working-capital assumptions while retaining the same accounting and financing identities.

The model is explanatory rather than causal. It does not use treatment and control groups or estimate population parameters. Scenario values are stress-test coordinates selected to illustrate the financial propagation mechanism. They should not be interpreted as typical AI effects or forecasts for a particular firm.

The architecture contains four linked modules: a network and process module describing effective coordination; an organizational module governing realization, lag, and persistence; an operating and accounting module translating changes into EBITDA and cash; and a financing module measuring bankability.

4.2. Formal multilayer coordination representation

Let G = (V, L, E, W) denote a directed weighted multilayer network, where V is the set of actors, L is the set of organizational or stakeholder layers, E contains intra-layer and inter-layer links, and W contains weights reflecting the materiality or quality of each link.

For each material process link e, four normalized attributes are considered: latency l_e, error or exception rate x_e, verification cost v_e, and accountable reachability a_e. Lower latency, error, and verification cost, and higher reachability represent improved coordination. A normalized effective-coordination index is defined as:

$$q = w_1\Delta(1-l) + w_2\Delta(1-x) + w_3\Delta(1-v) + w_4\Delta a, \sum_i w_i = 1, 0 \le q \le 1 \quad (1)$$

Index q is a calibration summary rather than a directly observed structural parameter. Its components may be estimated from process-mining logs, handoff times, forecast revisions, exception rates, reconciliation effort, audit evidence, or structured managerial assessment.

4.3. Organizational realization

Gross technical potential is not assumed to be fully realized. Let ρ denote organizational readiness, σ strategic resilience, and λ_t the implementation-lag factor in period t. Realized coordination is:

$$q_t^* = q \times \rho \times \sigma \times \lambda_t, 0 \le \rho, \sigma, \lambda_t \le 1 \quad (2)$$

This formulation permits two firms using similar technology to obtain different outcomes. It also permits delayed or partly reversed benefits when readiness is weak, resilience is low, or implementation requires a prolonged transition.

4.4. Bridge from coordination to operating assumptions

Revenue and cost effects are represented as bounded functions of realized coordination. The coefficients are calibration parameters rather than estimated structural effects:

$$u_t^R = \min\left(\overline{u}^R, \alpha q_t^*\right) \text{and } u_t^c = \min(\overline{u}^c, \beta q_t^*) \quad (3)$$

$$\text{Revenue}_t = \text{Revenue}_t^0(1 + u_t^R) \quad (4)$$

$$\text{OpEx}_t = \text{OpEx}_t^0(1 - u_t^c) + \text{Implementation OpEx}_t \quad (5)$$

$$\text{EBITDA}_t = \text{Revenue}_t - \text{OpEx}_t \quad (6)$$

The caps $\bar{u}^R$ and $\bar{u}^c$ prevent unbounded linear extrapolation. Empirical applications should calibrate α, β, and the caps by industry, function, and implementation maturity.

Table 4. Calibration logic and observable proxies.

Channel	Illustrative proxy	Primary financial transmission	Model role	Caution
Information latency	Order-to-decision time; forecast refresh frequency	Revenue / OpEx	Component of gross coordination potential q	Faster decisions may increase errors if controls are weak
Error and exception rate	Forecast error; rework; stockouts; quality exceptions	Revenue / OpEx	Component of gross coordination potential q	Requires consistent process definitions and comparable measurement periods
Verification cost	Reconciliation hours; audit effort; supplier-data checks	Primarily OpEx	Component of gross coordination potential q	AI may shift verification costs rather than eliminate them
Organizational readiness	Data quality; user adoption; decision rights; digital leadership; workforce preparation	Realization of operating effects	Realization coefficient ρ	Cannot be inferred from technology expenditure alone
Strategic resilience	Recovery time; process redundancy; shock response; adaptive capacity	Persistence of operating and cash-flow effects	Resilience coefficient σ	Resilience may itself require additional expenditure and organizational slack.
Implementation timing	Deployment schedule; ramp-up period; parallel systems; training; process migration	Timing of revenue, OpEx and cash-flow effects	Timing coefficient λ_t	Costs and benefits may arise in different periods, creating a temporary financing trough.
ESG credibility	Assurance; traceability; control effectiveness; disclosure quality; stakeholder accountability	Risk profile, credibility and, where evidenced, financing terms	Separate ESG/governance module	No automatic reduction in debt pricing, WACC, or increase in operating performance

The first six channels map directly onto the operating coordination mechanism. Organizational readiness, strategic resilience, and implementation timing filter gross coordination potential before it can affect operating and cash-flow outcomes. ESG credibility is deliberately kept outside this multiplicative relationship because it does not mechanically generate operating gains; it enters separately through governance, risk, disclosure credibility, and, where supported by observable evidence, financing conditions.

$$q_t^* = q \times \rho \times \sigma \times \lambda_t \tag{7}$$

where q denotes gross coordination potential, ρ organizational readiness, σ strategic resilience, and λ_t the timing of implementation and benefit realization. The equation is a calibration architecture, not an empirically estimated production function in this illustration. ESG-related credibility therefore

remains a distinct governance and financing channel and should affect financing assumptions only when supported by firm-specific evidence, contractual terms, or an explicitly identified sensitivity.

In this illustration, q*, α, and β are not separately estimated; the scenario coordinates are specified directly rather than generated mechanically by the coordination model. The preceding equations identify how such coordinates can be calibrated when observable firm-level evidence becomes available. Their role is thus to make the organizational-to-financial transmission explicit and auditable, without attributing empirical precision to parameters that have not been estimated.

4.5. Financing and bankability module

EBITDA is converted into cash available for debt service through explicit assumptions. Let κ denote the operating cash-conversion factor before specified capital and working-capital items.

$$\begin{aligned}\text{FCADS}_t = \kappa \cdot \text{EBITDA}_t - \text{Maintenance CapEx}_t \\ -\text{Implementation CapEx}_t - \Delta\text{NWC}_t - \text{Cash taxes}_t\end{aligned} \tag{8}$$

$$\text{DSCR}_t = \frac{\text{FCADS}_t}{\text{Debt service}_t} \tag{9}$$

$$\text{Interest coverage}_t = \frac{\text{EBITDA}_t}{\text{Cash interest}_t} \tag{10}$$

$$\text{Leverage}_t = \frac{\text{Net debt}_t}{\text{EBITDA}_t} \tag{11}$$

$$\text{DSCR buffer}_t = \text{DSCR}_t - \text{DSCR covenan} \tag{12}$$

$$\text{Leverage buffer}_t = \text{Leverage covenant} - \text{Leverage}_t \tag{13}$$

Minimum liquidity, trough-year DSCR, and covenant buffers are emphasized because averages may conceal temporary financing stress. The model can also incorporate probability distributions, but the illustration remains deterministic to preserve transparency.

4.6. Separation of AI and ESG effects

Three effects are kept distinct. AI operating effects alter revenue and recurring OpEx. Organizational readiness and resilience affect the realization, cost, timing, and persistence of those effects. ESG-related credibility can affect volatility, disclosure reliability, liquidity requirements, or financing terms. The third channel is not embedded in EBITDA unless it changes an identifiable operating line.

4.7. Scenario design

The reference plan uses average annual revenue of EUR 36.410 million, OpEx of EUR 32.041 million, and EBITDA of EUR 4.369 million. Four cases are considered:

Scenario A – Reference case: no incremental AI-related operating change.

Scenario D – Implementation friction: revenue −1%, OpEx +2%, EUR 1.2 million implementation CapEx, and EUR 0.5 million incremental working-capital absorption in the initial period.

Scenario B – Moderate operating improvement: revenue +5% and OpEx −2.5%.

Scenario C – Strong operating improvement: revenue +10% and OpEx −5%.

The improvement cases are illustrative stress-test coordinates, not estimates of typical performance or ordered probability states. The downside case is likewise illustrative. A continuous revenue / OpEx grid and parameter sensitivities should accompany any firm-specific application.

The selected coordinates are not intended to represent empirically estimated average effects of AI adoption. They illustrate how the reference financial structure responds to moderate and strong combinations of revenue and operating-cost changes. The individual percentages have no probabilistic meaning or general external validity. In firm-specific applications, the coordinates should be recalibrated using historical operating evidence, sector benchmarks, process-level indicators, or empirically estimated distributions.

5. Results

The results apply the proposed framework to the reference business plan, showing how alternative operating and implementation assumptions translate into financial performance, cash generation, and bankability.

5.1. Operating effects

Table 5 reports the direct arithmetic consequences of the scenario assumptions. The results do not indicate what firms generally achieve after adopting AI. They show what follows from the stated revenue and cost deltas when applied consistently to the reference plan.

Table 5. Scenario operating outcomes.

Scenario	Revenue (€m)	OpEx (€m)	EBITDA (€m)	EBITDA margin	Change vs baseline (€m)
A Reference case	36.410	32.041	4.369	12.0%	+0.000
D Implementation friction	36.046	32.682	3.364	9.3%	−1.005
B Moderate operating improvement	38.231	31.240	6.991	18.3%	+2.622
C Strong operating improvement	40.051	30.439	9.612	24.0%	+5.243

The implementation-friction case reduces EBITDA to approximately EUR 3.364 million because a modest revenue shortfall is combined with temporarily higher operating expenditure. The moderate operating-improvement case increases EBITDA by EUR 2.622 million, while the strong operating-improvement case increases EBITDA by EUR 5.243 million.

The apparent convexity of the favorable outcomes is mechanical: Revenue rises while operating cost falls. The table illustrates the importance of separating assumptions from evidence. A firm-specific application must support both channels independently and must avoid treating coordinated revenue and cost improvements as automatic.

5.2. Bankability dashboard

For comparability, the illustration assumes a 70% EBITDA-to-operating-cash conversion before specified items, EUR 0.8 million maintenance CapEx, EUR 0.4 million cash taxes and recurring deductions, annual debt service of EUR 1.5 million, cash interest of EUR 1.2 million, net debt of EUR 15 million, a DSCR covenant of 1.20x, and a leverage covenant of 4.0x. The implementation-friction case also includes the initial implementation CapEx and working-capital absorption described above.

Table 6. Illustrative bankability outcomes.

Scenario	FCADS (€m)	DSCR	Interest cover	Net debt/ EBITDA	DSCR buffer	Leverage buffer	Interpretation
A Reference case	1.858	1.24x	3.64x	3.43x	+0.04x	+0.57x	Marginal
D Implementation friction	−0.545	−0.36x	2.80x	4.46x	−1.56x	−0.46x	Material breach risk
B Moderate operating improvement	3.693	2.46x	5.83x	2.15x	+1.26x	+1.85x	Improved covenant buffers
C Strong operating improvement	5.528	3.69x	8.01x	1.56x	+2.49x	+2.44x	Improved covenant buffers

The baseline is only slightly above the assumed DSCR threshold. Under implementation friction, upfront CapEx and working-capital absorption produce negative FCADS and a covenant breach in the initial period, even though the project may retain a favorable longer-term rationale. The finding illustrates why timing matters: average EBITDA improvement cannot substitute for trough-year liquidity analysis.

The moderate operating-improvement case produces meaningful covenant buffers, with DSCR increasing to 2.46x and net debt/EBITDA falling to 2.15x. The strong operating-improvement case further strengthens all indicators. These results remain conditional on the assumed cash-conversion rate, debt service, and absence of additional implementation expenditure.

5.3. Break-even and sensitivity interpretation

The appropriate decision question is not whether favorable cases are possible in the abstract, but which combinations of revenue uplift, cost efficiency, implementation expenditure, and realization lag

preserve minimum liquidity and covenant compliance. The framework is designed to answer that question through transparent break-even and sensitivity analysis.

Table 7 broadens the discrete scenario comparison by reporting the mechanical EBITDA effect of alternative revenue and operating-cost combinations. The grid does not assign probabilities to individual outcomes; it shows how the reference cost structure responds across a continuous range of operating assumptions.

Table 7. EBITDA sensitivity to alternative revenue and operating-cost assumptions (€ million).

Revenue change	OpEx +2%	OpEx 0%	OpEx −2.5%	OpEx −5%
−1%	3.36	4.00	4.81	5.61
0%	3.73	4.37	5.17	5.97
+5%	5.55	6.19	6.99	7.79
+10%	7.37	8.01	8.81	9.61

Values represent EBITDA under the reference revenue and operating-cost structure. Revenue and OpEx variations are applied independently to their respective baseline amounts. The table assigns no probabilities to the reported combinations.

The sensitivity grid confirms that, within the reference cost structure, the financial effect depends jointly on the assumed revenue and operating-cost changes. It also demonstrates that Scenarios B and C are selected coordinates within a wider response surface rather than unique, predicted, or probabilistically ranked outcomes.

At the illustrative baseline, DSCR exceeds the 1.20x covenant by only 0.04x. Modest implementation friction can create a financing problem before operating benefits are realized. This is not a prediction; it is a conditional warning that a transformation program should be financed and sequenced with reference to the trough-year cash profile.

The network-to-finance bridge provides a disciplined route for calibration. A claimed cost saving should identify the affected process links, observed reductions in latency or exceptions, readiness and resilience assumptions, implementation timing, and the accounting line through which the saving enters EBITDA and cash. The bridge is therefore an audit trail for the assumption rather than a claim that network structure generates financial value.

The sensitivity holds the reference revenue base, 70% cash-conversion factor, debt service, maintenance CapEx, implementation CapEx, working-capital absorption, and cash deductions constant while varying only the starting EBITDA margin through the baseline OpEx structure. The result is deliberately mechanical, but it addresses a distinct question from Table 7: Identical implementation friction can have very different financing consequences depending on the firm's pre-existing margin and debt-service capacity. In this sense, financial absorptive capacity is a state variable of the transition, not an ex post description of success.

Table 8. Sensitivity of implementation-friction bankability to the starting EBITDA margin.

Starting EBITDA margin	EBITDA under Scenario D (€m)	DSCR	DSCR buffer vs 1.20x	Interpretation
6%	1.136	−1.40x	−2.60x	Severe transition stress
12% (reference)	3.364	−0.36x	−1.56x	Material breach risk
20%	6.335	1.02x	−0.18x	Near threshold but still below covenant
25%	8.192	1.89x	+0.69x	Transition absorbed within covenant

5.4. ESG financing channel

No ESG credibility effect is embedded in the EBITDA figures or automatically imposed through a lower WACC or debt margin. Verified governance and reporting practices may influence the debt margin, required liquidity buffer, covenant design, or perceived cash-flow volatility, but any such financing effect should be incorporated only when supported by observable contractual evidence, market data, or an explicitly identified sensitivity assumption.

Because the simulation is deterministic, it does not estimate cash-flow variance or a probability of default. In a stochastic or empirically calibrated extension, downside-risk effects could be measured through cash-flow volatility, the probability of covenant breach, expected shortfall, or changes in the required liquidity buffer. Here, we report covenant buffers and the implementation-friction scenario as transparent deterministic proxies for downside exposure.

6. Discussion

The results reinforce a central idea of this study: Technological capability is only the beginning of the financial story; what matters is whether the organization absorbs that capability, changes relevant operating processes, reaches accounting outcomes, and produces cash without exhausting liquidity or debt-service capacity along the way. The framework therefore shifts attention from AI adoption as an event to the conditions under which adoption becomes economically and financially credible.

The numerical illustration should be read within that boundary. It does not estimate a typical return to AI, nor does it empirically test the full set of propositions developed in Section 2.6. Its purpose is narrower: To show how specified operating and implementation assumptions propagate through a given financial structure. This distinction matters because the propositions operate at different points of the transmission chain. The simulation can illustrate some; others require organizational or governance data that the design deliberately does not claim to provide.

6.1. Theoretical contributions and implications

The first contribution is to treat AI as an organizational financial capability, rather than primarily as a technological asset or expenditure. Firms may deploy comparable technologies and still obtain very different results because data quality, managerial commitment, workforce readiness, decision

rights, and process redesign influence how much technical potential becomes usable organizational capability. This distinction between technical capability and realized coordination supports the transmission logic formalized in P1 and P2: Operating value depends not simply on what AI can technically do, but on whether the organization can translate that potential into coordinated action.

The distinction also clarifies the role of networks. Greater connectivity is not intrinsically valuable. Additional links can reduce information gaps, but they can also create congestion, cyber exposure, duplicated information, or blurred accountability. Network structure is therefore useful because it identifies where material relationships and frictions occur, not because topology is assumed to create financial value. Effective coordination becomes economically relevant only when changes in latency, errors, verification effort, or accountable reachability alter a real business process. In this sense, coordination is a transmission mechanism rather than an independent source of value.

The simulation only partly addresses this first part of the theoretical argument. It shows the financial consequences that follow once revenue and cost effects are specified, and therefore illustrates the financial logic associated with P1. It does not establish that AI-enabled coordination caused those effects, nor does it test the mediation mechanism proposed in P2, because the numerical exercise does not independently observe digital leadership and data-driven decision-making. Their role remains theoretically embedded in organizational readiness and requires firm- or process-level evidence for empirical validation.

A further contribution is to make accounting explicit within the transmission mechanism. Faster decisions, better forecasts, or fewer exceptions are economically interesting, but they are not financial outcomes. They become relevant to lenders when they can be traced to revenue, recurring operating expenditure, working capital, investment requirements, and FCADS. Accounting therefore provides more than measurement after the event: It disciplines the causal narrative by requiring each claimed organizational benefit to identify where, when, and through which financial line it should become visible.

This also explains why EBITDA is an incomplete endpoint. An AI initiative may improve expected operating profitability while absorbing substantial cash through implementation CapEx, data remediation, training, parallel systems, or working capital. The financing problem is therefore inherently intertemporal; what matters is not only the expected steady-state benefit, but whether the firm can finance the transition required to reach it.

Here, the simulation speaks more directly to the propositions. The implementation-friction case shows that costs and benefits arriving at different times can materially weaken FCADS and DSCR even when the longer-term transformation remains economically plausible. This is consistent with the timing mechanism in P3 and, more directly, with P5. The latter is the proposition the numerical analysis explores most clearly: Bankability depends on the interaction between expected operating gains, their timing, implementation expenditure, working-capital absorption, debt service, and the financial capacity available before implementation begins.

The starting-margin sensitivity sharpens this point. Identical implementation friction does not produce identical financing consequences. A firm entering the transition with stronger margins and greater debt-service capacity can absorb a temporary deterioration that may create covenant stress for a more constrained borrower. Financial absorptive capacity is therefore part of the economics of implementation, not merely an ex post description of a financially successful firm. This makes bankability dynamic: The relevant question is not simply whether debt can eventually be serviced, but how liquidity, DSCR, leverage, and covenant distance evolve while the transformation is taking place.

The persistence component of P3 remains less directly examined. The framework represents strategic resilience conceptually. Still, the deterministic simulation does not observe how organizations respond to cyber incidents, supplier failures, managerial turnover, or other shocks that could erode AI-related benefits over time. The results therefore illustrate the importance of timing, but should not be read as an empirical test of resilience.

Finally, separating AI operating effects from ESG-aligned governance is consistent with P4. Governance can improve traceability, accountability, control quality, and the credibility of projected benefits, but these effects should not be confused with an automatic increase in revenue or EBITDA. They may instead affect downside exposure, lender confidence, required liquidity, covenant design, or financing conditions. They also have costs, including assurance, cybersecurity, documentation, compliance, and human oversight. The simulation deliberately does not estimate this relationship or assign an ESG premium to financing terms. Therefore, P4 remains a theoretically grounded proposition for subsequent empirical testing rather than a result of the numerical exercise.

Taken together, these findings refine rather than confirm the propositions. The simulation partially illustrates P1 and P3, does not test P2 or P4, and most directly explores the financial mechanism proposed in P5. This asymmetry is important. It keeps our theoretical claims separate from what our numerical design can demonstrate while showing how the different propositions fit within one organizational-to-finance transmission chain.

6.2. Implications for managers, lenders, and investment committees

The framework's practical usefulness lies less in producing another AI score than in changing the questions asked before capital is committed. For managers, lenders, and investment committees, the relevant issue is not whether AI is present, but which processes it is expected to change, what evidence supports that expectation, when the financial effect should emerge, and whether the organization can finance the path between implementation and realization.

For management, this means beginning the investment case with the affected business processes rather than the technology. Each material benefit should have an identifiable process owner, an observable operational indicator, a financial-statement destination, and a credible implementation timetable. A claim that AI will improve forecasting, for example, becomes decision-useful only when management can explain whether better forecasting should reduce stockouts, inventory days, markdowns, or planning effort, and whether those effects should appear in revenue, OpEx, or working capital.

This is also where the distinction underlying P1 and P2 becomes operational. Purchasing software demonstrates investment, not organizational realization. User adoption is more informative, but does not establish operating improvement. Stronger evidence comes from changes in the processes the technology was intended to affect: decision latency, forecast error, exception rates, reconciliation effort, inventory days, or other relevant measures. Leadership and data-driven decision routines matter because someone must turn those outputs into organizational action.

Implementation costs require the same discipline. Software acquisition may be only one component. Data remediation, integration, cybersecurity, training, process redesign, parallel systems, assurance, and ongoing model governance can materially change the cash profile. Management should therefore evaluate the financing path to AI-enabled performance, rather than present only the economics of the expected steady state.

For lenders and credit analysts, the first due-diligence question should consequently be straightforward: Which cash-flow assumptions depend on AI, and what evidence supports them? The answer may require implementation milestones, process-mining data, decision and exception logs, forecast errors, inventory measures, reconciliation effort, user adoption, supplier performance, data-quality indicators, or documented process ownership. The appropriate evidence will vary by business and by the financial claim being made; there is no universal checklist.

A useful hierarchy follows. Technology contracts and implementation budgets show that money has been spent. Adoption measures show that a system is being used. Process evidence indicates whether organizational behavior is changing. Accounting evidence shows whether that change is reaching revenue, cost, or working capital. Cash-flow evidence establishes whether it is available to service debt. The lender should be able to follow that chain without accepting a generic "AI uplift" embedded in management forecasts.

The DSCR path is particularly important. A terminal or average DSCR can conceal the period in which implementation expenditure and working-capital absorption precede operating benefits. The implementation-friction scenario makes this point: FCADS can become negative, and covenant compliance can deteriorate before the anticipated operating gains are realized. This is the practical financing implication of the timing component of P3 and, especially, of P5.

Credit analysis should therefore examine minimum liquidity, trough-year DSCR, the depth and duration of the implementation trough, peak funding requirements, and the assumptions governing recovery. A temporary deterioration does not necessarily make a transformation unattractive. It changes the financing problem. The lender needs to know whether the trough has been identified, whether sufficient liquidity exists to bridge it, and whether the financing structure can accommodate it.

Pre-existing debt-service capacity matters as much. The starting-margin sensitivity shows why an AI investment cannot be assessed independently of the borrower undertaking it. The same implementation profile can be manageable for a firm with strong margins and liquidity and destabilizing for one already close to its covenants. Investment committees should therefore compare transformation programs not only by expected EBITDA uplift, but by how much financial capacity they consume before producing that uplift.

This reasoning has implications for covenant design. Where implementation risk is material, a single static ratio may provide less protection and less information than a structure aligned with the transition. Depending on the borrower and transaction, this may involve minimum-liquidity requirements, DSCR or leverage thresholds, reporting around material implementation milestones, controls over incremental expenditure or distributions, or staged access to additional financing. The framework does not imply a standardized set of "AI covenants"; it suggests that covenant design should reflect the actual timing and source of implementation risk.

Financing can similarly be staged when uncertainty concerns benefit realization rather than expenditure. Where appropriate, additional debt availability or contractual flexibility can be linked to observable implementation or operating milestones rather than solely to forecast outcomes. The distinction matters: money spent, capability installed, capability used, operating improvement realized, and cash generated are different events; a finance-readable AI case should not collapse them into one.

Governance evidence should be treated with comparable discipline. Consistent with P4, strong data controls, traceability, clear decision rights, cybersecurity, and independent assurance can make projected benefits more credible and may reduce certain downside risks. They should not automatically be converted into lower debt pricing, a lower WACC, or higher EBITDA. Any financing effect should

enter the analysis only where supported by contractual evidence, observable market information, or an explicitly identified sensitivity.

There are also clear boundaries to its use. The framework is not a credit-rating model, a probability-of-default model, or a substitute for conventional borrower analysis. Its coordination parameters do not establish causality when they are calibrated from managerial judgment. It is least informative when AI expenditure cannot be connected to identifiable processes, when expected benefits are highly speculative or very long-dated, or when firm-specific evidence is unavailable. In those circumstances, the appropriate conclusion is not to increase the assumed benefit, but to recognize that the claimed financial effect remains insufficiently evidenced.

Used within these limits, the framework changes AI due diligence in a useful way. The central question becomes not "Does this company use AI?" but "What changes operationally, how do we know, when does it reach cash, and can this borrower finance the transition?" The evidence chain summarized in Table 9 is therefore not an ancillary checklist. It is the practical counterpart of the propositions developed in Section 2.6 and the point at which organizational theory becomes usable in financial analysis.

6.3. Limitations and future research directions

The framework has deliberate boundaries, and the numerical analysis is explanatory rather than predictive: Scenario deltas are calibration coordinates, not estimated causal effects, and the reference business plan does not establish external validity. The coordination index also compresses heterogeneous organizational relationships into a tractable representation, while readiness, resilience, and implementation timing remain partly judgmental unless supported by firm-specific evidence. The deterministic model further abstracts from competitive responses, macroeconomic shocks, detailed tax effects, refinancing behavior, and debt sculpting.

These limitations also clarify what the simulation can and cannot say about the propositions. P5 receives the most direct numerical examination because implementation expenditure, working-capital absorption, debt service, and starting financial capacity are explicitly represented. P1 and P3 are only partly illustrated: The model can show what specified operating changes and implementation timing do to financial outcomes, but it cannot establish the organizational causes of those changes or the persistence of the resulting benefits. P2 and P4 remain untested because the simulation contains neither direct measures of digital leadership and data-driven decision-making nor an empirically estimated relationship between ESG-aligned governance and financing conditions. This asymmetry is intentional and provides a natural empirical agenda.

The next step is therefore to replace calibrated links progressively with observed ones. A useful starting point would be firm-quarter or firm-year datasets combining financial statements, dated indicators of material AI deployment, ESG measures, and process-level evidence. AI exposure could be proxied through patents, job postings, disclosed investment programs, earnings-call text, software implementation records, or verified process deployments. Relevant financial outcomes would include EBITDA margin, operating cash flow, cash conversion, leverage, interest coverage, credit spreads, ratings, covenant breaches, and investment intensity.

For P1, process-level measures are especially important. Decision latency, forecast revisions, exception rates, inventory days, reconciliation effort, supplier dependence, customer concentration, user adoption, and data quality could provide observable counterparts to effective coordination.

Such evidence would enable researchers to examine whether improvements in coordination are associated with revenue conversion or operating-cost efficiency, rather than assuming that relationship through calibration.

Testing P2 requires looking further inside the organization. Measures of digital leadership, decision rights, managerial use of AI outputs, and the maturity of data-driven decision routines could assess whether these factors mediate the relationship between technical AI capability and operating outcomes. This would help distinguish formal adoption from effective organizational use; a distinction that technology expenditure alone cannot reveal.

The dynamic mechanism in P3 calls for longitudinal evidence. Dated implementation records could be combined with measures of deployment speed, process migration, temporary duplication, operational disruptions, recovery time, and process redundancy. This would make it possible to study not only how quickly AI-related benefits emerge, but also whether they persist when the organization faces cyber incidents, supplier failures, managerial turnover, or other shocks.

P4 opens a different empirical avenue. Rather than asking whether ESG-aligned governance mechanically improves operating performance, research could test whether stronger traceability, assurance, accountability, and control quality are associated with financing outcomes such as credit spreads, covenant structures, required liquidity, debt maturity, or lender confidence. This would preserve the conceptual separation between operating value and financing credibility that is central to the framework.

P5 can be examined most directly through financing outcomes. Firm-quarter panels could test whether otherwise similar AI implementations produce different effects on DSCR, leverage, liquidity, or debt-service capacity depending on starting margins, indebtedness, and pre-existing financial capacity. Moreover, where adoption timing and pre-trends are sufficiently credible, staggered difference-in-differences designs could be useful; matched samples, event studies, or instrumental-variable approaches may complement them where their assumptions are defensible. The key question is not simply whether adopters perform better afterward, but whether financial absorptive capacity conditions the path from implementation to bankability.

Potential data sources are relatively accessible. Accounting and financing variables could be drawn from Compustat, Capital IQ, Orbis, Refinitiv, or SEC XBRL filings; AI-related activity from USPTO PatentsView, EPO PATSTAT, corporate filings, earnings-call transcripts, job-posting databases, or verified deployment records; and ESG indicators from MSCI, Sustainalytics, Refinitiv ESG, or firm-level sustainability reports. Combining these sources with process-level data would enable the coordination and realization parameters in the framework to be estimated rather than imposed.

Industry heterogeneity should also be treated as part of the theory rather than as statistical noise. Capital-intensive firms, regulated businesses, financial institutions, and asset-light digital companies differ materially in operating leverage, working-capital requirements, implementation costs, governance constraints, data intensity, and financing structures. The same organizational improvement may therefore produce very different cash-flow and bankability consequences. Searching for a single average "AI effect" across these settings may conceal the mechanisms that matter most.

In future empirical work, researchers can therefore develop the framework cumulatively. In this study, we identify which relationships require evidence, where that evidence enters the financial model, and which claims the simulation can and cannot support. The propositions provide the theoretical map, and the simulation makes part of that map financially visible; subsequent empirical

research can test the remaining links and determine how strongly they hold across firms, industries, and financing environments.

Figure 2 illustrates the bankability waterfall, showing how technological potential is progressively filtered through organizational readiness, realized coordination, operating effects, implementation costs, and cash conversion before ultimately affecting debt-service capacity and lender acceptance. The figure emphasizes that AI-enabled improvements become financially relevant only when they generate timely, resilient cash flows that preserve liquidity and debt-servicing capacity.

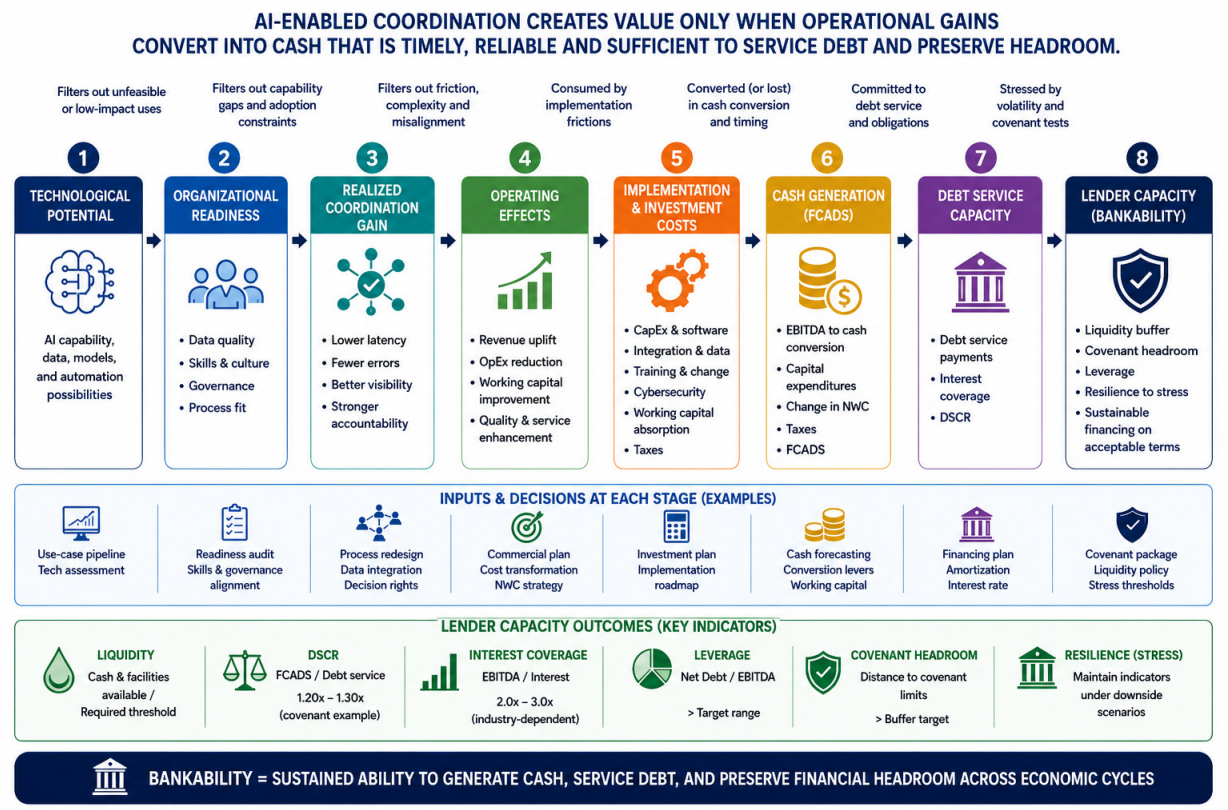


Figure 2. Bankability waterfall: from technological potential to lender capacity (Source: Authors' conceptualization and prompt; graphical rendering produced using OpenAI).

Table 9. Evidence required along the organizational-to-finance transmission chain.

Claim	Illustrative evidence	Financial translation	Lender question
Faster or better decisions	Cycle time, decision logs, forecast refresh frequency	Revenue leakage / OpEx	Is the operating change observable and attributable?
Better forecasting	Forecast error, stockouts, inventory days	Revenue / ΔNWC	Does the operational improvement convert into cash?
Procurement efficiency	Supplier prices, exception rates, reconciliation effort	Recurring OpEx	Is the saving recurring rather than shifted elsewhere?
AI implementation	Contracts, CapEx schedule, training and parallel-system costs	FCADS / liquidity	Where is the implementation trough and how is it financed?
Governance and controls	Assurance, traceability, decision rights, cyber controls	Risk/financing conditions	Are benefits credible, durable, and contractually financeable?

7. Conclusions

AI is increasingly transforming how firms generate, process, and coordinate information. However, the financial implications of that transformation remain difficult to evaluate because operational narratives and lender-oriented analysis use different concepts and metrics. In this paper, we develop a transparent framework that connects those perspectives.

The architecture models a sequential process: AI capability is filtered through organizational readiness and resilience; effective coordination changes revenue, operating costs, working capital, and risk; accounting identities translate those changes into EBITDA and cash; and lender-oriented indicators determine whether the resulting profile is bankable. Financial value comes from organizational execution, not technology adoption alone.

The numerical illustration shows why this distinction matters. Moderate and strong operating-improvement assumptions can materially improve EBITDA and debt-service capacity. However, the same investment can weaken liquidity and DSCR when implementation expenditure and working-capital absorption precede benefits. The additional starting-margin sensitivity shows that identical implementation friction can have very different financing consequences depending on pre-existing financial absorptive capacity. Timing, cash conversion, and trough-year debt-service capacity are therefore integral to AI investment appraisal.

The contribution is methodological rather than causal, but it addresses a genuine prospective finance problem. The framework provides an auditable way to translate process-level assumptions into financial consequences while separating AI operating effects, organizational realization, and ESG-related credibility. It can support project design, lender assessment, stress testing, and future empirical calibration.

AI is often evaluated according to what algorithms can achieve. Financial institutions evaluate organizations according to their capacity to generate sustainable cash flows and honor future

commitments. AI capability is therefore not financial value in itself: Organizational coordination is the transmission mechanism, accounting is the translation mechanism, and cash generation is the financing test. The financing value of AI depends not only on the eventual operating gain, but also on whether the firm can finance the path required to reach it.

Author contributions

RMV (corresponding author) has mainly written sections 1, 3, 4 and 6; SCR sections 2 and 7; JLP section 5. All authors have read and approved the final version of the manuscript for publication.

Use of AI tools declaration

The authors declare they have used Artificial Intelligence (AI) tools in the creation of this article. OpenAI image-generation tools were used solely for the graphical rendering of Figures 1, 2, and A.1, based on the authors' own conceptual designs and prompts. The authors reviewed all outputs and take full responsibility for the content of the article.

Acknowledgments

The authors thank the participants at the RIBAF conference (Università Cattolica del Sacro Cuore, Milan, 27 September 2024) and the anonymous reviewers for constructive comments. The usual disclaimer applies.

Conflict of interest

The authors declare no competing interests related to this publication.

Data availability statement

The study does not use confidential firm-level observations. The numerical illustration is reproducible from the assumptions, equations, and tables reported in the manuscript. A firm-specific application would require the baseline business plan, debt schedule, operational evidence, and calibration inputs described in the appendices.

Funding

The authors received no specific funding for this research.

References

Acciarini C, Cappa F, Boccardelli P, et al. (2023) How can organizations leverage big data to innovate their business models? A systematic literature review. *Technovation* 123: 102713. https://doi.org/10.1016/j.technovation.2023.102713

Barabási AL (2016) *Network science*. Cambridge University Press. https://www.networksciencebook.com/

Barabási AL, Albert R (1999) Emergence of scaling in random networks. *Science* 286: 509–512. https://doi.org/10.1126/science.286.5439.509

Bianconi G (2018) *Multilayer networks: Structure and function*. Oxford University Press. https://doi.org/10.1093/oso/9780198753919.001.0001

Cano-Marin E (2024) The transformative potential of generative artificial intelligence (GenAI) in business: A text mining analysis on innovation data sources. *ESIC Market* 55: e333. https://doi.org/10.7200/esicm.55.333

Choi JY, Lee CY, Oh MS (2025) Discovering causal relationships among financial variables associated with firm value using a dynamic Bayesian network. *Data Sci Finance Econ* 5: 1–18. https://doi.org/10.3934/DSFE.2025001

Dwivedi YK, Al-Banna H (2025) Generative artificial intelligence (GenAI) for sustainability: An exploration of emerging academic discourses. *Joinetech* 1: 1–10. https://doi.org/10.65479/joinetech.14

Enholm IM, Papagiannidis E, Mikalef P, et al. (2022) Artificial intelligence and business value: A literature review. *Inf Syst Front* 24: 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Feldhütter P, Pedersen LH (2025) Is capital structure irrelevant with ESG investors? *Rev Financ Stud* 38: 2362–2385. https://doi.org/10.1093/rfs/hhae059

Ferreira L, Torres P, Augusto M (2025) The moderating effect of power distance on the relationship between CEO career horizon and ESG performance. *Sustain Technol Entrep* 4: 100107. https://doi.org/10.1016/j.stae.2025.100107

Gallego Gómez C, Tapia López A, Márquez García JA (2024) Determining factors for the use of social networks as information platforms by Generation Z. *ESIC Market* 55: e359. https://doi.org/10.7200/esicm.55.359

Inard L (2023) Cash flow valuation and ESG. In: Glavas D (Ed.), *Valuation and sustainability: A guide to include environmental, social, and governance data in business valuation*. Cham: Springer, 99–128. https://doi.org/10.1007/978-3-031-30533-7_4

Kar AK, Choudhary SK, Singh VK (2022) How can artificial intelligence impact sustainability: A systematic literature review. *J Clean Prod* 376: 134120. https://doi.org/10.1016/j.jclepro.2022.134120

Lui AKH, Lee MCM, Ngai EWT (2022) Impact of artificial intelligence investment on firm value. *Ann Oper Res* 308: 373–388. https://doi.org/10.1007/s10479-020-03862-8

Medina-Molina C, Pérez-Macías N, Rey-Tienda S, et al. (2025) Do ethical issues influence the interest of young people in using artificial intelligence? An integrated application of qualitative comparative analysis. *Sustain Technol Entrep* 4: 100108. https://doi.org/10.1016/j.stae.2025.100108

Mishra S, Ewing MT, Cooper HB (2022) Artificial intelligence focus and firm performance. *J Acad Mark Sci* 50: 1176–1197. https://doi.org/10.1007/s11747-022-00876-5

Moro-Visconti R, Cruz Rambaud S, López Pascual J (2023) Artificial intelligence-driven scalability and its impact on the sustainability and valuation of traditional firms. *Humanit Soc Sci Commun* 10: 795. https://doi.org/10.1057/s41599-023-02214-8

Nguyen PTM, Tran MCD, Hoang TT, et al. (2025) ESG and firm value: A literature overview and valuation approach. *In ASEAN International Sandbox Conference,* 7: 134–145. Available from: http://www.aseansandbox.org/.

Palos-Sánchez PR, Chang-Tam RJ, Folgado-Fernández JA (2025) The role of neobanks and FinTech in sustainable finance and technology: The customer/user perspective for entrepreneurs. *Sustain Technol Entrep* 4: 100109. https://doi.org/10.1016/j.stae.2025.100109

Pérez-García S (2025) Application of agentive artificial intelligence and retrieval-augmented generation for predictive maintenance operations. *Joinetech* 1: 187–191. https://doi.org/10.65479/joinetech.29

Sætra HS (2023) The AI ESG protocol: Evaluating and disclosing the environment, social, and governance implications of artificial intelligence capabilities, assets, and activities. *Sustain Dev* 31: 1027–1037. https://doi.org/10.1002/sd.2438

Wang S, Gao M, Zhang H (2025) Enhancing creativity and sustainable competitive advantage through data-driven decision-making and digital leadership. *IEEE Trans Eng Manag* 72: 1361–1375. https://doi.org/10.1109/TEM.2025.3551331

Wang S, Zhang H (2025) Enhancing environmental, social, and governance performance through artificial intelligence supply chains in the energy industry: Roles of innovation, collaboration, and proactive sustainability strategy. *Renew Energy* 245: 122855. https://doi.org/10.1016/j.renene.2025.122855

Wang S, Zhang H (2026) Artificial intelligence for information-driven resilience: Enhancing strategic adaptation and entrepreneurial success. *Int J Inf Manag* 89: 103057. https://doi.org/10.1016/j.ijinfomgt.2026.103057



AIMS Press

© 2026 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0)