Global Multidisciplinary Journal
eISSN: 2791-173X pISSN: 2791-2760

VOLUME04 ISSUE11
Published 30-11-2025 *Page No. 51-59*

Transforming Merger and Acquisition Practice through Artificial Intelligence: A Theoretical and Applied Framework for AI-Enabled Due Diligence and Decision-Making

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ABSTRACT

Background: The accelerating integration of artificial intelligence (AI) and adjacent data technologies into financial services and corporate strategy has created a transformative moment for mergers and acquisitions (M&A). Existing literature documents discrete advances—digital transformation in banking and finance, AI-enhanced financial reporting, and big data approaches to enterprise value assessment—but a comprehensive, practice-focused synthesis tailored to M&A due diligence and deal structuring remains underdeveloped (Alam, 2025; Antwi et al., 2024; Rodríguez-Mazahua et al., 2016).

Objectives: This article develops an original, publication-grade theoretical and applied framework explaining how generative and analytic AI reshape each stage of the M&A lifecycle—sourcing, valuation, due diligence, negotiation, integration—and how organizational capabilities and human capital must evolve to capture value. The study aims to bridge technical, managerial, and strategic perspectives to guide practitioners, private equity actors, and policy-oriented scholars (Ellencweig et al., 2024; Emmi, 2025).

Methods: Drawing on cross-disciplinary theory from digital transformation, finance, and organizational learning, this work synthesizes prior empirical and conceptual research to construct a narrative model of AI-enabled M&A. The methodology is text-based and integrative: comparative theoretical analysis, critical synthesis of domain literature, and scenario-driven mapping of AI tools to M&A tasks (Corea, 2017; Farboodi & Veldkamp, 2020).

Results: The framework identifies five transformative vectors: (1) Data-driven deal sourcing and screening; (2) Automated and semi-automated financial and operational due diligence; (3) AI-assisted valuation models that augment rather than replace human judgement; (4) Contract and legal automation to accelerate negotiation and risk identification; and (5) Post-merger integration (PMI) intelligence systems that operationalize value capture. Each vector presents unique capability requirements, governance demands, and biases/risks which the framework disaggregates and remediates with proposed organizational and technical controls (Betts & Jaep, 2017; Antwi et al., 2024; Shounik, 2025).

Conclusions: AI fundamentally recalibrates resource allocation, timing, and expertise in M&A. Successful adoption requires firms to invest concurrently in data architecture, continuous human learning, specialized AI governance, and hybrid teams that combine domain and data-science skills. The article concludes with a practical roadmap for private equity firms and corporate acquirers and outlines future research avenues for empirical validation and regulatory design (Baskin, 2023; Brown et al., 2019; Chowdhury et al., 2024).

KEYWORDS

Artificial intelligence, mergers and acquisitions, due diligence, private equity, digital transformation, financial reporting, organizational learning

INTRODUCTION

The practice of mergers and acquisitions has always been at the crossroads of finance, law, strategy, and organizational science. Historically, M&A outcomes have been shaped by access to information, speed of execution, and the ability to execute complex integrations (Ippolito, 2020; Zambelli, 2024). The evolution of data capture technologies, cloud computing, and machine learning is now altering the underlying economics of these determinants by enabling previously infeasible analyses at scale (Rodríguez-Mazahua et al., 2016; Farboodi & Veldkamp, 2020). The confluence of generative AI, natural language processing, and advanced analytics introduces capabilities that can dramatically compress the timeline of due diligence, expose hidden operational leverage, and assist with legal and contractual assessment—promising both efficiency gains and new avenues of value creation (Ellencweig et al., 2024; Emmi, 2025).

Yet, while numerous practitioner accounts and early empirical studies highlight promising applications, there is no consolidated theoretical framework that maps AI capabilities directly onto M&A tasks and decision nodes while simultaneously articulating organizational implications. Existing research on digital transformation in finance underscores macro-level benefits—operational efficiency and customer experience improvements—but often treats M&A as an incidental context or leaves it to practitioners to translate insights into transactional workflows (Alam, 2025; Antwi et al., 2024). Conversely, legal-technical literature has explored automation of contract drafting and review, but often in isolation from valuation, integration planning, and the human capital adjustments needed for practical adoption (Betts & Jaep, 2017).

This gap has three dimensions. First, there is an empirical lacuna: systematic, rigorous studies that document how AI tools alter the accuracy and timing of valuation and risk assessment are scarce (Shounik, 2025). Second, there is a conceptual fragmentation: literature on AI in finance, AI in law, and organizational learning rarely converge into a unified model tailored to M&A (Corea, 2017; Brown et al., 2019). Third, there are governance and ethical concerns—data privacy, model opacity, and algorithmic bias—that are insufficiently integrated into prescriptive guidance for deal professionals (Chowdhury et al., 2024).

This article addresses these gaps by offering a comprehensive, theoretically informed, and practice-oriented framework for AI-enabled M&A. It situates AI within the full lifecycle of a transaction—from origination and screening to due diligence, negotiation, and integration—illustrating how AI augments human decision-making while identifying potential failure modes. The article advances three principal claims. First, AI shifts the bottlenecks in M&A from information acquisition toward interpretation, judgment, and governance (Farboodi & Veldkamp, 2020). Second, the highest value accrues to organizations that adopt a hybrid architecture combining automated analytics with curated human expertise (Brown et al., 2019; Baskin, 2023). Third, emergent roles and capability sets—particularly those blending data science, domain expertise, and legal acumen—will reconfigure entry-level and professional career trajectories in private equity and investment banking (Shounik, 2025; Zambelli, 2024).

By synthesizing insights across diverse literatures and offering explicit operational prescriptions, the article seeks to serve both academic researchers and transaction professionals: it is sufficiently theoretical to enable empirical operationalization and sufficiently applied to inform immediate organizational choices.

METHODOLOGY

This research adopts a text-based integrative methodology combining theoretical synthesis, comparative analysis, and scenario mapping. The study is intentionally non-empirical in the sense that it does not present novel field data or experiments. Instead, it constructs an interpretive framework that can guide empirical research and practical implementation. The methodology proceeds in three interrelated steps:

Conceptual Synthesis: The first stage involved a systematic reading and cross-mapping of literature spanning AI in finance, digital transformation in banking, analytics pedagogy, contract automation, private equity due diligence, and the economics of financial data (Antwi et al., 2024; Alam, 2025; Brown et al., 2019; Betts & Jaep, 2017; Ippolito, 2020; Farboodi & Veldkamp, 2020). Core themes were extracted—data availability, automation of repetitive tasks, enhanced predictive capacity, and governance requirements—and then clustered according to their relevance across the M&A lifecycle.

Task-to-Technology Mapping: Building on the synthesis, the second step mapped specific AI and analytics capabilities (e.g., natural language processing, generative models, anomaly detection, time-series forecasting, graph analytics) to discrete M&A tasks (e.g., target identification, financial statement validation, contract review, integration tracking). This mapping prioritizes interpretability and practical relevance. For each pairing, the analysis identifies potential gains, failure modes (such as model bias or data sparsity), and required organizational enablers (talent, data architecture, leadership commitment).

Scenario Development and Prescriptive Roadmap: The final step deploys scenario modelling—constructing plausible organizational archetypes (e.g., digitally native private equity firm, incumbent corporate acquirer with legacy systems, boutique advisory firm) to test how the proposed framework plays out under different capability endowments and constraints. These scenarios permit the derivation of prescriptive roadmaps for capability development, governance frameworks, and human capital investment.

Throughout the methodological process, the article grounds claims in existing literature and uses logical argumentation to extend theory into practical recommendations. Where empirical quantities would normally be required (e.g., effect sizes), the article explicates the mechanisms that would generate such effects, thereby enabling subsequent empirical studies to operationalize and test the hypotheses presented (Sharma & Prashar, 2015; Rodríguez-Mazahua et al., 2016).

RESULTS

Because this work is a theoretical and applied synthesis, the "results" section reports the outputs of the conceptual synthesis, the task-to-technology mapping, and the scenario analyses. The outcomes are organized as follows: (A) a lifecycle map of AI applications in M&A; (B) a taxonomy of task-technology pairings with benefits and risks; and (C) capability archetypes and associated roadmaps.

A. Lifecycle Map of AI Applications in M&A

Deal Origination and Sourcing: AI enables the automated scanning of public and proprietary data sources to identify acquisition targets based on predictive indicators of strategic fit and performance trajectories. Machine learning models trained on historical transaction outcomes and firm-level signals (financial ratios, patent filings, sentiment indicators) can flag targets with higher probability of synergy realization. This capability accelerates deal flow and can reduce search costs for both corporate acquirers and private equity firms (Farboodi & Veldkamp, 2020).

Preliminary Screening and Valuation: AI-driven analytics augment traditional screening metrics by incorporating alternative data—web traffic, supply chain signals, social media sentiment—to refine early valuation ranges. Predictive models, particularly ensemble methods and time-series forecasting, can generate probabilistic scenarios for revenue and cash flow trajectories under alternative assumptions (Antwi et al., 2024).

Due Diligence—Financial and Operational: Natural language processing (NLP) and pattern-detection algorithms automate the extraction and cross-validation of financial and contractual information. Models detect anomalies in accounting entries, highlight inconsistencies between management assertions and transactional data, and surface operational performance patterns that warrant deeper review. Generative AI can summarize voluminous documents, allowing deal teams to focus on interpretative tasks (Betts & Jaep, 2017; Antwi et al., 2024).

Legal and Contractual Review: Automated contract analysis tools using NLP and structured extraction simplify identification of key clauses, contingent liabilities, and change-of-control provisions. Advanced models can flag non-standard language or clauses that deviate from industry norms and suggest redlining templates for negotiation (Betts & Jaep, 2017).

Valuation Modeling and Risk Quantification: By combining structured financial models with probabilistic scenarios informed by machine learning outputs, organizations can derive richer distributions of estimated enterprise value that reflect operational and market uncertainties. AI models can incorporate macroeconomic indicators and sectoral trends to adjust discount rates and growth assumptions dynamically (Farboodi & Veldkamp, 2020).

Deal Structuring and Negotiation Support: Decision-support systems provide negotiators with scenario-based outcomes, negotiation playbooks, and predictive assessments of counterpart behavior based on textual and historical patterns. These systems, while not making decisions, supply structured guidance to improve negotiation outcomes (Ellencweig et al., 2024).

Post-Merger Integration and Value Capture: AI supports PMI by tracking KPI trajectories, detecting deviation from integration plans, and recommending resource reallocation. Machine learning models can predict integration risks—cultural misfit, customer churn—by analyzing communications, employee sentiment data, and customer behavior. This enables earlier interventions to preserve value (Ippolito, 2020).

B. Taxonomy of Task-Technology Pairings: Benefits and Risks

The mapping identifies specific pairings of AI techniques with M&A tasks and articulates the expected benefits and principal risks.

NLP and Document Understanding: Applicable to contract review, diligence memo summarization, and regulatory compliance. Benefits include speed and consistency in extracting clauses and terms; risks include hallucination in generative models, failure to capture legal nuance, and overreliance on automated summaries absent human verification (Betts & Jaep, 2017).

Anomaly Detection and Time-Series Analysis: Useful for forensic accounting, revenue recognition validation, and operational metric monitoring. Benefits include early detection of outliers and potential fraud; risks include false positives from model mis-specification and the necessity of domain-specific thresholds to avoid alarm fatigue (Antwi et al., 2024).

Graph Analytics and Network Models: Used for mapping ownership structures, supply chains, and customer relationships. Benefits derive from revealing hidden interdependencies and exposure clusters; risks revolve around incomplete data leading to misinterpretation and privacy constraints when aggregating third-party data (Rodríguez-Mazahua et al., 2016).

Generative Models and Summarization Tools: Employed for drafting due diligence summaries and synthesizing long-form documents. Benefits are time savings and structured condensation of information; risks include inaccuracies (hallucinations), lack of traceability, and liability if summaries omit material facts (Betts & Jaep, 2017).

Predictive Models for Performance Forecasting: Applied to revenue, margin, and churn forecasting. Benefits include probabilistic scenario analysis and integration of alternative data sources; risks emerge from training data bias, failure to generalize across structural breaks, and model opacity that impedes stakeholder trust (Farboodi & Veldkamp, 2020).

C. Capability Archetypes and Roadmaps

Digitally Native Private Equity Firm: This archetype starts with modern data infrastructure and in-house data science. Roadmap emphasizes refining proprietary deal-scoring models, building automated diligence pipelines, and investing in explainable AI. The primary advantage is speed—lower transaction costs and ability to underwrite more deals per analyst. The principal challenge is governance and independence of models from market noise.

Incumbent Corporate Acquirer with Legacy Systems: This archetype faces data fragmentation and cultural resistance. The roadmap prioritizes data consolidation, pilot programs in low-risk diligence tasks (e.g., document tagging), and leadership-driven upskilling. Gains are incremental but can be substantial once integration systems support PMI intelligence; risks include protracted transformation timelines and misalignment with existing deal processes (Alam, 2025).

Boutique Advisory Firm: Lacking scale but rich in domain knowledge, boutique firms can leverage AI-as-a-service solutions to augment human expertise. Roadmap involves curated adoption of specialist tools (contract analytics, forensic accounting modules) and repositioning as hybrid advisors—combining high-touch advice with rapid analytics. Risk centers on vendor dependence and loss of unique advisory value if tools commoditize advice (Brown et al., 2019).

DISCUSSION

The integrative framework presented yields several interlocking insights with theoretical and managerial implications. The discussion unpacks these implications across three domains: the reconfiguration of informational advantage, the evolution of human capital and organizational design, and governance considerations related to model risk and ethics. It then highlights limitations and proposes future empirical tests.

Reconfiguration of Informational Advantage

Historically, M&A outcomes have been heavily contingent on asymmetric access to information and the speed at which it can be processed (Ippolito, 2020). AI alters both axes. On the access side, alternative data and network analytics democratize signals that were previously inaccessible or too costly to process (Farboodi & Veldkamp, 2020). On speed, automation compresses the time required to digest large volumes of legal, financial, and operational documents (Betts & Jaep, 2017). These shifts translate into a redefinition of competitive advantage: it is less about raw data access and more about the ability to curate, govern, and translate model outputs into strategic judgement (Brown et al., 2019).

This reconfiguration produces new forms of rent capture. Firms that can integrate AI outputs into decision-making loops and align incentives across deal teams will extract more value than those that merely adopt point tools without organizational adaptation. For example, a firm that uses predictive models to triage targets but

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eISSN: 2791-173X pISSN: 2791-2760

VOLUME04 ISSUE11
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lacks the human expertise to validate model-flagged risks will either overpay or miss legitimate opportunities. Hence, the advantage is realized where AI workflows and human judgement are tightly coupled, a theme echoed in research advocating for "analytics academies" and continuous learning ecosystems (Brown et al., 2019; Baskin, 2023).

Evolution of Human Capital and Organizational Design

AI does not eliminate the need for human capital; it transforms it. Our framework identifies emerging role hybrids: analyst-data scientists with domain fluency, legally trained technologists who understand contract semantics and model limitations, and integration managers who can operationalize model output into change programs (Shounik, 2025; Zambelli, 2024). The entry-level skillset for M&A analysts is shifting: proficiency in querying datasets, interpreting model diagnostics, and communicating uncertainty is becoming essential (Shounik, 2025).

Organizational design needs to evolve accordingly. Hierarchies that separate data science from deal teams create coordination costs and degrade model value. Instead, cross-functional squads co-located in the deal execution flow—comprising deal professional, data scientist, and legal technologist—improve responsiveness and interpretation. This hybrid architecture also supports ongoing learning: as models are used in live transactions, feedback loops can refine models and calibrate human heuristics (Brown et al., 2019; Baskin, 2023).

Governance, Model Risk, and Ethical Considerations

With increased reliance on automated systems comes heightened governance imperatives. Several risk categories require attention: model accuracy and bias, data privacy and consent, legal liability arising from automated summaries or missed contractual clauses, and operational risks stemming from overreliance on opaque models. The literature on automation and contract drafting emphasizes the promise of machine learning while warning about legal nuance and the limits of automated interpretation (Betts & Jaep, 2017).

To mitigate these risks, the framework advocates a layered governance approach. First, model validation protocols should be embedded within deal timelines: independent model verification, stress-testing across alternative economic scenarios, and adjudication by cross-functional committees are necessary (Antwi et al., 2024). Second, transparency mechanisms—explainable AI tools, mandatory model rationale documentation, and traceable data lineage—build trust among stakeholders. Third, legal safeguards and explicit contractual language should be used to allocate liability when automated tools are used in diligence, preventing obscured accountability.

Importantly, governance costs are not merely compliance burdens; they represent a necessary investment to maintain market credibility and to prevent systemic adverse outcomes. Private equity and corporate acquirers will need to demonstrate to limited partners, boards, and regulators that their AI practices are robust, auditable, and aligned with fiduciary responsibilities (Ippolito, 2020; Zambelli, 2024).

Practical Roadmap for Adoption

The theoretical insights translate into a pragmatic roadmap:

1. Start with high-value, low-risk pilots: Implement AI for document triage and contract clause extraction rather than full reliance for legal advice. This builds internal familiarity while minimizing liability exposure (Betts & Jaep, 2017).
2. Invest in data infrastructure: Consolidate financial, operational, and alternative data onto interoperable platforms. The marginal benefit of analytics increases dramatically when data silos are removed (Alam,

2025).

3. Build hybrid teams: Recruit and train professionals who combine domain expertise and data literacy. Upskilling existing analysts through targeted programs—analytics academies—yields sustained capability (Brown et al., 2019; Baskin, 2023).
4. Establish governance and model-validation routines: Independent validation, explainability standards, and scenario stress-testing should become standard elements of deal committees (Antwi et al., 2024).
5. Reconfigure talent pipelines: Redefine entry-level roles to include data skills and adjust compensation and career paths to attract interdisciplinary talent (Shounik, 2025).

Limitations and Future Research Directions

The primary limitation of this work is its conceptual and non-empirical nature. While the framework integrates extant literature and logical argumentation, empirical validation is necessary. Future studies should collect transaction-level data to quantify the impact of AI on deal timelines, valuation accuracy, and post-merger performance. Several specific empirical questions emerge:

- To what extent do AI-enabled diligence processes reduce information asymmetry and affect acquisition premiums? (Farboodi & Veldkamp, 2020).

- How do AI-augmented valuation models compare to traditional discounted cash flow in predictive accuracy, particularly under regime shifts? (Antwi et al., 2024).

- What are the measurable effects of hybrid team structures on deal execution speed and integration outcomes? (Brown et al., 2019).

- What governance mechanisms are most effective in minimizing model-induced legal or reputational risk? Comparative case studies across private equity and strategic acquirers would be informative (Zambelli, 2024; Emmi, 2025).

Further theoretical development should also explore the macroeconomic implications: as data aggregation and predictive analytics proliferate, market behaviour could change—affecting price discovery and potentially amplifying systemic risks if many firms rely on similar model architectures (Farboodi & Veldkamp, 2020).

CONCLUSION

Artificial intelligence is not a peripheral convenience but a core capability that will reshape the logic of mergers and acquisitions across the lifecycle. The framework presented elucidates how AI and related technologies map to discrete M&A tasks, the benefits they confer, and the governance and human capital investments required to realize value. Crucially, the gains from AI will accrue not to the firms that merely adopt tools, but to those that integrate AI outputs into a disciplined decision-making architecture—combining technical systems, hybrid expertise, and rigorous governance.

The future of M&A will be defined by firms that can bridge the analytic and the interpretive: using AI to surface signals and compress timelines while ensuring that final decisions remain anchored in domain knowledge and fiduciary prudence. This requires deliberate investments in data infrastructure, talent development, and model governance. For scholars, the agenda ahead is rich: empirical validation of the framework's claims, exploration of macro-level market effects, and refinement of governance norms adapted to high-stakes commercial transactions.

The transition will be evolutionary rather than instantaneous. Organizational learning, continuous upskilling, and strategic experimentation will determine winners. Private equity firms, corporate acquirers, and advisors that approach AI with a balanced posture—ambitious in application yet conservative in governance—stand to secure durable competitive advantages in the age of AI-enabled diligence and deal-making.

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