Artificial Intelligence in Mergers and Acquisitions: Enhancing Decision-Making, Due Diligence, and Strategic Integration in the US Capital Market

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Abstract: Background: The application of artificial intelligence (AI) to mergers and acquisitions (M&A) is transforming classical workflows—from target identification and valuation to due diligence, integration planning, and post-transaction monitoring. A growing corpus of practitioner reports and academic research highlights both opportunities and risks when AI is embedded into M&A decision chains. This article synthesizes contemporary findings and provides an extended theoretical, methodological, and practical analysis of AI-enabled M&A practice within the US capital market context.

Objectives: The primary objective is to articulate how AI techniques—natural language processing, unsupervised clustering, predictive modeling, and knowledge representation—can materially enhance decision-making and efficiency across M&A stages; to examine the interplay of AI with adjacent technologies such as blockchain; to enumerate attendant risks and governance requirements; and to propose a descriptive, reproducible case-study oriented methodology for evaluating AI's contributions to M&A outcomes.

Methods: Using a structured, case-study-oriented methodology informed by recent practitioner reports and foundational technical literature, the article constructs an analytical framework that links algorithmic functions to specific M&A tasks. The methods narrative integrates algorithmic primitives (e.g., transformer-based language models, clustering algorithms, information-theoretic measures) with qualitative process mapping and risk assessment techniques. The approach draws on previous empirical observations and practitioner accounts to model typical data flows and decision points where AI produces measurable benefits.

Results: Descriptive findings show that AI markedly reduces time and cognitive load for target screening, enhances evidence aggregation and anomaly detection during diligence, supports scenario modeling in valuation, and improves post-merger integration (PMI) monitoring through automated event detection. However, the gains are moderated by data quality constraints, interpretability deficits, regulatory uncertainty, and integration frictions between technical and domain experts.

Conclusions: AI is neither a panacea nor a mere automation tool; it is a structural change agent that requires organizational redesign, investment in data governance, and new skill profiles for analysts. To capture value, firms must codify AI's role in decision governance, invest in explainability, and actively manage legal and ethical risk. Future research should empirically quantify effect sizes across M&A outcomes and test governance interventions in field experiments.

Keywords: mergers and acquisitions, artificial intelligence, due diligence, natural language processing, target identification, blockchain, data governance

INTRODUCTION:

The decision to acquire, merge with, or divest a corporate asset represents one of the most consequential strategic moves a firm can make. Historically, the M&A lifecycle—target identification, valuation, negotiation, due diligence, closing, and post-merger integration—has relied on expert judgment, structured financial analysis, and documentary review (Vasarhelyi, Kogan, & Tuttle,

2015). The sheer volume and heterogeneity of data now available to deal teams, coupled with advances in artificial intelligence, have motivated an industry-wide reevaluation of how cognitive labor and algorithmic analysis are allocated across M&A activities (Bughin et al., 2017; Hitt, Tambe, & Brynjolfsson, 2012). The aim of this article is to present a comprehensive, theoretically grounded, and practically oriented account of how AI is reshaping M&A decision-making within the US capital markets.

A number of practitioner and academic contributions have documented the early adoption patterns of AI across M&A tasks. For example, several case studies and practitioner reports describe AI's ability to expedite due diligence by automatically extracting contractual clauses and flagging anomalies (Baumgartner, 2024; Korosec, 2021). Others highlight the use of NLP models to surface strategic fit signals or to synthesize public filings, media coverage, and patent records for target identification (Wyatt, Ahmad, & Presta, 2022; Rahman, 2021). Meanwhile, recent interdisciplinary work draws attention to the confluence of blockchain and AI as a means to create verifiable data provenance in cross-border deals (Kajewole et al., 2023). These contributions lay the groundwork for a systematic synthesis that maps algorithmic capabilities onto M&A stages and discusses the governance structure necessary to capture value and manage risk.

Despite the promise, unexplored gaps persist. Most scholarly work has either been narrowly technical (describing models) or narrowly prescriptive (offering checklists for practitioners) without integrating technical, organizational, and regulatory dimensions (Marquardt, Mathieu, & Dery, 2023). There is limited rigorous discussion linking algorithmic primitives—such as transformer-based language models or clustering algorithms—to concrete M&A cognitive tasks and decision thresholds. Additionally, much of the literature has yet to propose operational metrics to evaluate AI's contribution beyond anecdotal productivity gains (Shounik, 2025). This article addresses these gaps by offering an integrative framework that elucidates where AI changes the informational foundation of M&A decisions and what governance and organizational changes are needed to realize benefits.

The problem statement is straightforward: while AI offers potentially large efficiency gains across multiple M&A stages, firms often lack a structured approach to deploy, evaluate, and govern AI systems in ways that preserve decision quality and legal compliance. The literature reveals several recurring frictions: (1) data provenance and quality limitations that reduce model reliability (Li, 2018; Marquardt et al., 2023); (2) interpretability deficits that create trust barriers between analysts and algorithmic outputs (Devlin et al., 2019; MacKay, 2003); and (3) skill mismatches, particularly for entry-level analysts whose roles are shifting from manual review to AI oversight (Shounik, 2025). The remainder of the article offers a detailed methodology and descriptive results derived from synthesizing case evidence and technical literature. It then provides a deep discussion that elaborates theoretical implications, counter-arguments, limitations, and future research directions.

METHODOLOGY

The methodological approach of this study is deliberately synthetic and descriptive. Facing a rapidly evolving intersection of technical and business practice, the objective is less to perform a single empirical experiment than to construct a reproducible analytic framework that connects AI techniques to specific M&A tasks and to articulate criteria for assessing AI's contribution. The methodology entails three strands: (1) a task-mapping exercise that decomposes the M&A lifecycle into granular decision points; (2) a mapping of algorithmic primitives to these decision points, drawing on foundational algorithmic literature; and (3) a qualitative synthesis of practitioner reports and academic observations to derive expected performance effects, risks, and governance implications. The chosen approach mirrors a case-study orientation because it emphasizes rich contextualization and prescriptive insights over narrow causal identification (Narteh-Kofi et al., 2024).

Task decomposition. The M&A lifecycle is decomposed into the following canonical stages: market scanning and target identification; preliminary contact and valuation modeling; data collection and due diligence (legal, financial, operational, tax); negotiation and deal structuring; closing and contractual execution; and post-merger integration (PMI) and monitoring. Within each stage, decision points are identified where information processing, anomaly detection, semantic understanding, or prediction play an outsized role. For example, in due diligence, contract review requires clause extraction, comparability analysis, and inconsistency detection—each a candidate for algorithmic augmentation (Baumgartner, 2024).

Algorithmic mapping. For each task, the methodology prescribes a set of algorithmic primitives. Natural language processing (NLP), particularly transformer

models such as BERT (Devlin et al., 2019), is recommended for dense text understanding tasks (e.g., extracting representations from SEC filings, contracts, or news articles). Unsupervised clustering algorithms (Jain, Murty, & Flynn, 1999) are relevant for grouping similar targets or segmenting large portfolios of documents. Probabilistic modeling and information-theoretic measures (MacKay, 2003) help calibrate uncertainty and determine when model outputs require human escalation. Supervised predictive models, including ensemble methods and neural predictors, can be used for forecasting synergies, revenue trajectories, or default probabilities when labeled historical deal data are available (Bughin et al., 2017). The methodology emphasizes that model selection should be governed by task fit, data availability, and explainability requirements.

Data and evidence synthesis. The methodology relies on practitioner reports, technical papers, and conceptual works as evidence for performance claims. Practitioner documents (e.g., EY, Norton Rose Fulbright, Berkeley Research Group) provide applied accounts of AI workflows and reported benefits (Baumgartner, 2024; Wyatt et al., 2022; Marquardt et al., 2023). Technical literature supports the plausibility of algorithmic performance claims (Devlin et al., 2019; Jain et al., 1999; MacKay, 2003). Where possible, chains of inference are constructed: for example, if transformer models have been shown to extract semantic representations of legal text with high accuracy (Devlin et al., 2019), one can infer that such models materially reduce manual contract review time in diligence when used correctly (Korosec, 2021).

Governance and metrics. The methodology prescribes a set of organizational and technical governance mechanisms: data lineage tracking, model versioning, human-in-the-loop escalation thresholds, and legal review checkpoints (Marquardt et al., 2023). Metrics for assessing AI contributions are proposed in descriptive terms: time-to-first-pass for diligence, proportion of anomalous contracts identified, variance reduction in valuation scenarios, and qualitative measures such as analyst satisfaction and perceived decision confidence (Shounik, 2025). The methodology stresses that empirical testing—A/B style where feasible—should be used to quantify effect sizes in situ.

Ethical and regulatory constraints. The methods section includes a normative checklist to ensure compliance with securities laws, disclosure requirements, and antitrust considerations. Because many M&A deals occur within regulated environments, the methodology requires legal counsel to validate AI outputs that directly affect financial statements or disclosures (Li, 2018; Marquardt et al., 2023).

Limitations of methodology. The approach is intentionally descriptive and integrative; it does not produce novel causal estimates via randomized trials. Instead, it provides a framework practitioners and researchers can use to design empirical evaluations and to trace where value and risk emerge. The methodology thereby trades experimental precision for breadth and applicability across diverse firm contexts.

RESULTS

This section presents descriptive results obtained by applying the methodological mapping to common M&A tasks and by synthesizing evidence from the referenced literature. Results focus on the types of improvements AI can enable, the constraints that limit these improvements, and the typical governance requirements necessary to harness AI effectively.

Target identification and market scanning. AI improves the breadth and speed of target identification by aggregating structured and unstructured signals—public filings, news, patent filings, job postings, and proprietary databases—and computing similarity scores relative to the acquirer's strategic profile (Wyatt et al., 2022; Rahman, 2021). Transformer-based embeddings (Devlin et al., 2019) permit semantic matching that moves beyond keyword heuristics, enabling analysts to uncover nonobvious candidates that traditional screens would miss (Bughin et al., 2017). Unsupervised clustering (Jain et al., 1999) helps to segment industries and reveal clusters of firms with latent strategic commonalities, while information-theoretic measures (MacKay, 2003) can quantify the information gain associated with adding a potential target to a watchlist.

Practically, the literature reports reductions in time-to-screen from weeks to days for large portfolios when AI is used to prefilter candidates (Wyatt et al., 2022; Korosec, 2021). However, these gains are conditional on data access—AI is only as broad as the underlying data and will underperform when relevant private signals are unavailable (Marquardt et al., 2023).

Due diligence and document review. Due diligence is where many early AI deployments have concentrated because the task contains high volumes of documents and repetitive extraction tasks. NLP models excel at clause extraction, obligation summarization, and anomaly detection in contracts and financial reports

(Baumgartner, 2024; Korosec, 2021). Transformer models trained or fine-tuned on legal corpora can extract clause types and categorize risk levels with a level of recall and precision that approaches experienced human reviewers on benchmark tasks (Devlin et al., 2019). In practical terms, applied reports suggest first-pass review times drop substantially; for example, large legal and accounting firms report time savings ranging from 30% to 60% on initial document triage (Baumgartner, 2024; Wyatt et al., 2022).

Nonetheless, results consistently warn that model outputs require human validation. Financial nuance—contingent liabilities, off-balance sheet items, and jurisdictional regulatory subtleties—can confound automated systems, particularly when training data do not include sufficient examples from relevant jurisdictions or specialized contract forms (Li, 2018; Marquardt et al., 2023). Moreover, false negatives in diligence—missed covenants or undisclosed obligations—can have catastrophic financial consequences, underscoring the need for human-in-the-loop escalation (Korosec, 2021; Marquardt et al., 2023).

Valuation and predictive modeling. AI's role in valuation is to complement, not replace, traditional discounted cash flow (DCF) and comparable company analyses by providing probabilistic scenario forecasting and by extracting and structuring large external datasets (e.g., market trends, alternative data sources) that inform revenue and cost projections (Bughin et al., 2017; Hitt et al., 2012). Machine learning models can forecast revenue trajectories, churn dynamics, or customer acquisition costs using historical firm and market data. Where labeled historical M&A outcomes exist, supervised learning can predict integration success indicators or post-deal abnormal returns with some predictive power (Sood & Tellis, 2011). Yet, predictive accuracy often depends on the availability and relevance of historical analogs; in novel strategic acquisitions or highly dynamic markets, models struggle to generalize (Arthur, 2017).

Negotiation and deal structuring. AI can support negotiation by simulating counterparty preferences, generating term sheet variants, and estimating the risk-return payoff of different contractual provisions (Wyatt et al., 2022). Text generation and summarization tools provide negotiators with concise distillations of alternative contract drafts, while predictive models can estimate the likelihood of counterpart concessions given past behavior and contextual signals. Nevertheless, dealmaking includes human creativity, signaling, and strategic bluffing—

areas where AI currently plays a supportive role rather than an autonomous one (Sood & Tellis, 2011).

Post-merger integration and monitoring. AI augments PMI by automating performance monitoring, identifying integration pain points through anomaly detection in operational metrics, and assisting in human capital integration via skills mapping and attrition risk modeling (Shounik, 2025; Marquardt et al., 2023). Natural language analysis of employee communications and external employee reviews can surface cultural mismatch risks early (Wyatt et al., 2022). These predictive signals allow acquirers to prioritize interventions, yet they raise privacy and ethical considerations that must be managed through governance frameworks (Marquardt et al., 2023).

Interplay with blockchain and data provenance. AI's effectiveness depends heavily on the quality and provenance of input data. Blockchain has been proposed as a complementary technology that provides verifiable, tamper-evident records for transactional data and document timestamps—useful in cross-border deals with complex supply chains (Kajewole et al., 2023). When blockchain is combined with AI, provenance information enhances model trustworthiness by enabling auditors to trace the origin of inputs used for model decisions. However, practical deployments are nascent, and interoperability, scale, and legal recognition remain open issues (Kajewole et al., 2023).

Risks observed in practice. Practitioner reports and conceptual analyses identify critical risk domains: model bias and fairness, overreliance on imperfect models, data leakage and confidentiality breaches, regulatory compliance failures, and interpretability deficits (Marquardt et al., 2023; Li, 2018). There is also a workforce risk: roles traditionally occupied by entry-level analysts are shifting toward model supervision and data curation, requiring new skills (Shounik, 2025). Strategic risks include the systemic effects of AI-driven dealmaking—if many acquirers use similar models and data, markets may experience herding and reduced deal diversity (Bughin et al., 2017; Sood & Tellis, 2011).

DISCUSSION

The integration of AI into M&A practice produces layered theoretical and practical implications. This discussion expands on those implications, addresses counter-arguments, and lays out a research and practice agenda.

AI as an information amplification mechanism. At a foundational level, AI functions as an amplifier of information processing capacity: it increases the breadth and depth of signals a human decision maker

can consider within practical time bounds (Bughin et al., 2017). From an economic standpoint, the data revolution (Hitt et al., 2012) combined with AI reduces information frictions, potentially lowering transaction costs and enabling more efficient resource allocation. Transformer models and unsupervised clustering permit decision makers to process semantics across millions of textual artifacts—SEC filings, patents, and customer reviews—allowing them to build richer priors about targets (Devlin et al., 2019; Jain et al., 1999). Yet amplification is not uniformly beneficial. Information overload becomes algorithmic overload if outputs are not curated and prioritized with clear decision thresholds. The correct governance response is to define decision thresholds informed by uncertainty quantification and human escalation rules (MacKay, 2003).

Interpretability, trust, and human oversight. A recurring theme in the literature is the tension between sophisticated models and interpretability. High-performing models—deep neural nets or transformers—often operate as black boxes, producing outputs that are difficult to audit (Devlin et al., 2019). In high-stakes environments like M&A, interpretability is not a mere convenience; it is a legal and managerial necessity. The proposed remedy is a hybrid approach: use complex models for high-recall screening and pair them with interpretable surrogate models or rule-based explanations for decision support (Marquardt et al., 2023). Information-theoretic diagnostics (MacKay, 2003) can help quantify model uncertainty and prioritize cases for human review.

Organizational change and skill profiles. AI's integration requires organizational redesign. Traditional analyst roles focused on manual review and spreadsheet modeling are shifting toward roles that emphasize data engineering, model validation, and cross-functional translation between technical outputs and business implications (Shounik, 2025). Firms must invest in training and in recruiting hybrid profiles that combine domain expertise with data literacy. Failure to do so risks degrading decision quality as analysts become mere consumers of unvetted model outputs.

Regulatory and legal considerations. The use of AI in M&A intersects with securities regulation, disclosure obligations, antitrust considerations, and data privacy law. For instance, automated extraction of material information from target firms could accelerate required filings or disclosures, but reliance on algorithmic summaries does not absolve legal responsibilities (Li, 2018). Moreover, cross-border deals introduce jurisdictional variances in data protection—an acquirer that uses AI models trained on European personal data must ensure compliance with GDPR-like frameworks when applying insights in US transactions (Marquardt et al., 2023). Legal counsel must be integrated into AI governance to ensure that algorithmic outputs used for material decisions meet disclosure and fiduciary standards.

Counter-arguments and critical perspectives. Skeptics argue that AI may introduce systemic biases and promote homogeneity in deal selection. If many acquirers rely on similar datasets and models, market outcomes may cluster around certain narratives—potentially amplifying bubbles or herd behavior (Sood & Tellis, 2011; Bughin et al., 2017). A second critique focuses on overhyping model capabilities: AI may be very good at surface tasks (e.g., clause extraction) but poor at reasoning about contextually complex contractual obligations or cultural fit. Responding to these critiques requires empirical evaluation: longitudinal studies to test whether AI adoption correlates with improved post-deal performance, and scenario analyses to measure systemic risk.

The role of blockchain: complement or distraction? Blockchain offers strong guarantees about data immutability, which can increase trust in transactional records used to train models (Kajewole et al., 2023). Where provenance matters—supply chain audits or IP verification—blockchain may materially enhance AI reliability. However, blockchain deployments add engineering complexity and require legal recognition of on-chain records in courts and regulatory filings. The practical result is that blockchain is complementary where provenance is essential, but it is not universally necessary for all AI-enhanced M&A tasks.

Ethics, privacy, and employee monitoring. AI-enabled PMI often uses employee data and communications to assess cultural fit and attrition risks. These practices raise privacy concerns and ethical questions about surveillance and consent (Marquardt et al., 2023). Companies must balance legitimate integration interests with employee rights, employing privacy-preserving analytics and robust data governance to maintain trust.

Practical recommendations for practitioners. Based on the synthesis, the article offers several actionable recommendations:

1. Adopt a staged approach to AI deployment: start with AI-assisted screening and document triage where gains are clear and risks are manageable (Korosec, 2021; Baumgartner, 2024).

2. Establish human-in-the-loop thresholds: define

recall/precision tradeoffs that mandate human review beyond specified risk scores or model confidence intervals (MacKay, 2003).

3. Invest in data governance and provenance: maintain lineage, access controls, and validation procedures for datasets used in model training (Marquardt et al., 2023; Kajewole et al., 2023).

4. Build interpretability into workflows: use explainability tools and surrogate models to make outputs actionable for nontechnical stakeholders (Devlin et al., 2019).

5. Redesign analyst roles and training programs: focus on model validation, data curation, and domain translation skills (Shounik, 2025).

6. Integrate legal counsel early: ensure model outputs that affect disclosure or contractual terms are reviewed by legal teams (Li, 2018).

7. Pilot and measure: use controlled pilots with pre-specified metrics (time-to-first-pass, anomaly detection rates, valuation variance reduction) to quantify AI's contribution (Wyatt et al., 2022; Shounik, 2025).

LIMITATIONS

The principal limitation of this study is its descriptive and integrative character. Unlike empirical research that uses randomized methods or large proprietary datasets to estimate causal effects, this article synthesizes practitioner accounts and technical literature to build plausible mappings between AI capabilities and M&A tasks. As such, effect sizes cited (e.g., time savings in due diligence) are descriptive aggregates of practitioner reports rather than rigorously validated estimates. Another limitation is the dependence on publicly available practitioner materials that may reflect optimistic vendor or consultancy perspectives. A further limitation concerns the rapidly evolving nature of AI; models and best practices described in this article may evolve quickly as new architectures and governance norms emerge.

Future Research Directions

To advance the field, several research avenues are recommended:

1. Field experiments and natural experiments. Researchers should collaborate with firms to run controlled trials where AI-assisted workflows are compared to traditional workflows, measuring outcomes such as diligence time, post-deal performance, and incidence of material misstatements (Bughin et al., 2017).

2. Longitudinal studies on analyst career trajectories.

Empirical work is needed to chart how roles evolve when AI is adopted at scale, providing evidence to guide workforce development (Shounik, 2025).

3. Comparative legal analyses. Cross-jurisdictional studies should analyze how differing regulatory regimes affect AI use in M&A, including disclosure, privacy, and admissibility of electronic provenance (Li, 2018; Marquardt et al., 2023).

4. Systemic risk modeling. Economists and complexity scientists should study whether widespread adoption of similar AI models produces market-level behavior changes—herding, volatility, or reduced diversity in deal types (Sood & Tellis, 2011; Arthur, 2017).

5. Explainability and audit trails. Technical research should prioritize methods that produce reliable explanations suitable for legal scrutiny and fiduciary accountability (Devlin et al., 2019; MacKay, 2003).

6. Blockchain integration case studies. Carefully documented deployments combining blockchain and AI for provenance should be analyzed for costs, benefits, and legal recognition (Kajewole et al., 2023).

CONCLUSION

Artificial intelligence is reshaping M&A practice by enabling faster, broader, and deeper information processing across all stages of the life cycle. From target screening using semantic embeddings to automated clause extraction in due diligence, AI offers tangible productivity gains (Devlin et al., 2019; Baumgartner, 2024). Yet, these gains are contingent on robust data governance, interpretability safeguards, human oversight, and integration with legal and organizational processes (Marquardt et al., 2023; Shounik, 2025). AI should be deployed as a decision-augmentation technology rather than as an autonomous decision maker; firms that codify the role of AI within governance frameworks and invest in the requisite skills and infrastructure are most likely to capture value.

The evolution of AI in M&A raises broader questions about market dynamics, regulation, and the future of professional roles in finance and law. As research and practice mature, empirical field studies and cross-disciplinary collaborations will be essential to quantify benefits, manage risks, and ensure that AI contributes to sound, lawful, and equitable M&A outcomes. The framework proposed in this article—mapping algorithmic capabilities to M&A tasks and pairing them with governance measures—provides a practical starting point for both researchers and practitioners navigating this complex but promising landscape.

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