Traditional Valuation Models versus AI-Based Valuation Techniques: The Future of Investment Banking

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Abstract: Artificial intelligence is reshaping the financial industry at a pace that few technologies have matched. For decades, investment banks have relied on a well-established toolkit of Discounted Cash Flow (DCF) analysis, Comparable Company Analysis (CCA), Precedent Transaction Analysis (PTA), and Leveraged Buyout (LBO) modelling to estimate the value of companies. These methods remain in daily use, yet their fit within an increasingly data-driven and AI-enabled financial system has become an open question. Rising market volatility, the proliferation of alternative data sources, and the rapid maturation of machine-learning algorithms all raise a common concern: whether valuation frameworks designed for an earlier information environment will remain effective in the years ahead. This study sets the traditional valuation models that dominate investment banking against the AI-based techniques now gaining ground across the industry. AI-based approaches draw on a range of technologies machine learning, deep learning, natural language processing (NLP), predictive analytics, and, most recently, generative AI to produce valuations that can be more accurate, faster to generate, and capable of absorbing far larger volumes of financial information than conventional methods allow. The research adopts a qualitative approach grounded in secondary data drawn from finance and adjacent fields, with each source assessed against criteria specific to the valuation model under discussion. The findings suggest that traditional and AI-based valuation each contribute something the other lacks. Traditional methods offer an established, theoretically grounded basis for estimating asset value and enjoy broad acceptance among regulators. AI-based methods, by contrast, integrate data from disparate sources and tend to improve the accuracy of value predictions. Taken together, the evidence indicates that AI-based systems are extending rather than displacing traditional valuation, enabling firms to manage and assess assets more effectively. The study concludes that investment banking is likely to move toward hybrid valuation frameworks that pair established financial theory with advanced AI. Such integration promises gains in valuation precision, operational efficiency, and strategic decision-making, while preserving the professional judgment and regulatory accountability on which the profession depends.

Keywords: Artificial Intelligence (AI); Investment Banking; Business Valuation; Discounted Cash Flow (DCF); Machine Learning; Financial Modeling; Predictive Analytics; Corporate Finance

INTRODUCTION

Business valuation lies at the heart of investment banking, influencing strategic decisions related to mergers and acquisitions (M&A), initial public offerings (IPOs), private equity investments, corporate restructuring, portfolio management, and financial reporting. Accurate valuation enables investors, corporate executives, financial analysts, and regulatory authorities to determine the intrinsic worth of a business while supporting efficient capital allocation and informed investment decisions. For several decades, investment banks have relied on well-established valuation methodologies, including Discounted Cash Flow (DCF) analysis, Comparable Company Analysis (CCA), Precedent Transaction Analysis (PTA), Dividend Discount Models (DDM), and Leveraged Buyout (LBO) models. These approaches are grounded in financial theory and have become industry standards because they provide structured frameworks for estimating enterprise and equity values under varying market conditions. Despite their widespread acceptance, the rapidly changing financial environment has exposed several limitations of traditional valuation methods, particularly their dependence on historical financial information, simplifying assumptions, and the subjective judgments of financial analysts (1,2)....

The global financial landscape has undergone profound transformation over the past decade due to digitalization, globalization, and the increasing availability of large-scale financial data. Modern financial markets generate enormous volumes of structured and unstructured information through stock exchanges, financial statements, earnings reports, economic indicators, news articles, analyst reports, social media platforms, satellite imagery, consumer behavior, and alternative data sources. These diverse datasets contain valuable information regarding firm performance, investor sentiment, competitive dynamics, and macroeconomic conditions. However, conventional valuation techniques were developed in an era when financial information was relatively limited and primarily derived from accounting records and market prices. Consequently, traditional valuation models often struggle to capture the complexity, speed, and interconnectedness of modern financial markets, creating opportunities for more sophisticated analytical approaches that can exploit large and continuously evolving datasets (3,4).

Among traditional valuation approaches, the Discounted Cash Flow (DCF) model remains the cornerstone of investment banking valuation. DCF estimates the intrinsic value of a company by projecting future free cash flows and discounting them to their present value using an appropriate discount rate, generally the weighted average cost of capital (WACC). The theoretical strength of the DCF model lies in its focus on the economic fundamentals of a business rather than temporary market fluctuations. Nevertheless, the model is highly sensitive to assumptions regarding revenue growth, operating margins, terminal value, and discount rates. Small variations in these assumptions may produce substantial changes in estimated firm value, thereby introducing uncertainty into investment decisions. Similar limitations exist in Comparable Company Analysis and Precedent Transaction Analysis, where valuation depends heavily on selecting appropriate peer companies and comparable transactions, both of which require considerable professional judgment and may not fully reflect firm-specific characteristics (5,6).

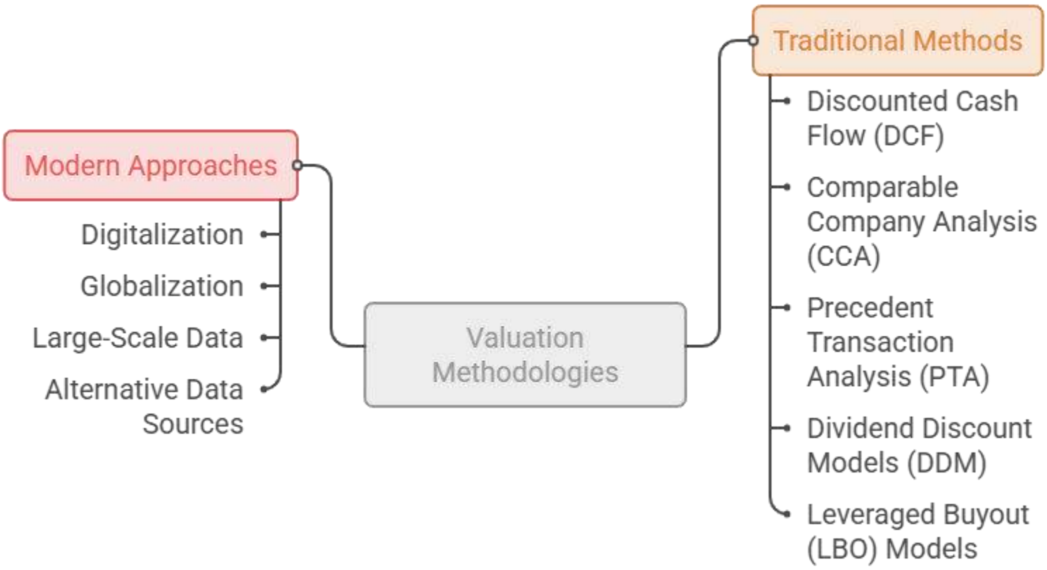

Figure 01. Valuation methodologies in modern finance

The increasing complexity of financial markets has encouraged investment banks to explore advanced computational methods capable of processing large datasets and identifying complex nonlinear relationships among financial variables. Artificial Intelligence (AI), particularly machine learning, deep learning, natural language processing (NLP), reinforcement learning, and predictive analytics, has emerged as one of the most transformative technologies in modern finance. Unlike traditional statistical techniques that require explicit assumptions regarding variable relationships, AI systems can learn directly from historical and real-time data, continuously improving predictive performance through iterative learning processes. These capabilities enable AI-based valuation techniques to incorporate not only conventional financial indicators but also alternative data such as corporate disclosures, earnings-call transcripts, social media sentiment, macroeconomic trends, ESG indicators, supply chain information, and market news, thereby generating more comprehensive and dynamic estimates of firm value (7,8).

Machine learning algorithms including Random Forests, Gradient Boosting Machines, Support Vector Machines, Artificial Neural Networks, and Extreme Gradient Boosting (XGBoost) have demonstrated considerable potential in forecasting stock prices, bankruptcy risk, creditworthiness, earnings performance, and corporate valuations. Deep learning architectures further enhance these capabilities by extracting complex hierarchical patterns from multidimensional datasets that may not be evident through conventional econometric approaches. Similarly, Natural Language Processing has enabled financial institutions to quantify qualitative information contained in annual reports, management discussions, analyst recommendations, and news articles by converting textual information into measurable financial signals. More recently, generative AI and Large Language Models (LLMs) have begun supporting financial professionals by automating report generation, financial modelling, scenario analysis, due diligence, and investment research, significantly improving operational efficiency within investment banking divisions (9,10).

The integration of AI into valuation practices represents more than a technological advancement; it reflects a fundamental shift in how financial information is collected, analyzed, and interpreted. AI systems possess the ability to evaluate millions of observations simultaneously, identify hidden relationships among variables, detect emerging market trends, and continuously update valuation estimates as new information becomes available. These capabilities offer significant advantages during periods of heightened market volatility, where rapid changes in economic conditions may render static valuation assumptions obsolete. Furthermore, AI models reduce manual computational effort, accelerate financial analysis, and support real-time decision-making, thereby enabling investment banks to respond more effectively to changing market environments (11,12).

Despite these advantages, AI-based valuation techniques are accompanied by several important challenges that limit their widespread adoption. Many advanced machine learning algorithms operate as "black-box" models, making it difficult for financial professionals, auditors, and regulators to understand how specific valuation estimates are generated. Model interpretability has therefore emerged as a critical concern, particularly in highly regulated financial markets where transparency, accountability, and auditability are essential. In addition, AI systems depend heavily on the quality, completeness, and representativeness of training data. Poor-quality data, biased datasets, or rapidly changing market conditions may reduce predictive accuracy and produce misleading valuation outcomes. Ethical concerns surrounding algorithmic bias, data privacy, cybersecurity, and regulatory compliance further complicate the implementation of AI within investment banking operations (13,14).

Investment banks must therefore balance the computational power of AI with the analytical rigor and professional judgment embodied in traditional valuation frameworks. Financial valuation is not solely a mathematical exercise but also requires consideration of industry dynamics, strategic positioning, management quality, regulatory developments, competitive behavior, geopolitical risks, and investor expectations. Many of these factors remain difficult to quantify using purely algorithmic approaches. Experienced investment bankers contribute contextual understanding, qualitative assessment, and strategic insight that complement quantitative valuation outputs. Consequently, rather than replacing financial professionals, AI increasingly functions as a decision-support technology that enhances analytical capabilities while leaving final investment judgments to experienced practitioners (15,16).

The financial services industry has already witnessed substantial AI adoption across multiple functional areas, including algorithmic trading, fraud detection, credit scoring, portfolio optimization, customer relationship management, anti-money laundering, and risk management. Valuation represents the next logical domain for AI integration because it directly influences capital allocation and strategic corporate decisions. Major investment banks and financial technology firms continue investing heavily in AI infrastructure to improve forecasting accuracy, automate repetitive analytical tasks, and generate competitive advantages through superior data analytics. Simultaneously, regulatory authorities are developing governance frameworks that promote responsible AI adoption while maintaining market integrity, investor protection, and financial stability (17,18).

Although numerous studies have independently examined either traditional valuation techniques or AI applications in finance, relatively limited research has systematically compared these approaches within the context of investment banking. Existing literature often focuses on algorithmic performance without adequately considering practical implementation challenges, regulatory requirements, explainability, or the complementary role of financial expertise. There remains a need for comprehensive analysis that evaluates the respective strengths, limitations, and future roles of conventional valuation models and AI-based techniques in supporting investment banking activities. Understanding these differences is increasingly important as financial institutions seek to modernize valuation practices while maintaining compliance with accepted financial standards and professional ethics (19,20).

Against this backdrop, the present study aims to compare traditional valuation models with emerging AI-based valuation techniques and evaluate their implications for the future of investment banking. Specifically, the study examines the theoretical foundations, operational characteristics, strengths, limitations, and practical applications of both valuation paradigms using evidence from contemporary academic and professional literature. Furthermore, the study explores whether AI should be viewed as a replacement for traditional valuation models or as a complementary technology capable of enhancing existing financial practices. It is argued that the future of investment banking is unlikely to be defined by the complete displacement of conventional valuation methodologies. Instead, the industry is expected to adopt hybrid valuation frameworks that combine the theoretical robustness, transparency, and regulatory acceptance of traditional financial models with the predictive power, scalability, and analytical sophistication of artificial intelligence. Such an integrated approach has the potential to improve valuation accuracy, operational efficiency, strategic decision-making, and long-term value creation while preserving the professional judgment that remains central to investment banking practice (21).

Methodology

This study adopts a qualitative research methodology based on a systematic review and comparative analysis of secondary data to examine the differences between traditional valuation models and Artificial Intelligence (AI)-based valuation techniques in investment banking. A qualitative approach was considered appropriate because the primary objective of the research is to synthesize existing theoretical, empirical, and practical knowledge rather than to develop or test a statistical model. By integrating findings from prior academic research and industry reports, the study provides a comprehensive understanding of how AI is transforming valuation practices while assessing whether traditional financial models remain relevant in modern investment banking (1,2).

The study relies exclusively on secondary data obtained from credible academic and professional sources. Peer-reviewed journal articles, conference proceedings, scholarly books, working papers, industry reports, and publications from recognized financial institutions and international organizations were used as the primary sources of information. Literature was identified through major academic databases, including Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, Wiley Online Library, Taylor & Francis Online, Emerald Insight, JSTOR, and Google Scholar. Only English-language publications directly related to business valuation, investment banking, financial modelling, artificial intelligence, machine learning, deep learning, natural language processing, predictive analytics, and financial forecasting were considered for inclusion in the review (3–5).

To ensure the quality and relevance of the selected literature, specific inclusion and exclusion criteria were established. Studies were included if they focused on traditional valuation approaches such as Discounted Cash Flow (DCF), Comparable Company Analysis (CCA), Precedent Transaction Analysis (PTA), Dividend Discount Models (DDM), Residual Income Models, or Leveraged Buyout (LBO) valuation, as well as AI-based techniques including machine learning algorithms, artificial neural networks, natural language processing, explainable AI, predictive analytics, and generative AI applications in finance. Preference was given to peer-reviewed publications presenting theoretical developments, empirical evidence, methodological advancements, or practical applications relevant to investment banking. Articles lacking sufficient methodological rigor, duplicate publications, opinion-based articles, non-English documents, and studies unrelated to valuation or financial decision-making were excluded from the analysis (6–8).

The selected studies were analyzed using thematic content analysis, which enabled the identification of recurring concepts, methodological approaches, advantages, limitations, and emerging trends across the literature. Initially, all selected publications were reviewed in detail to extract information regarding research objectives, valuation methodologies, datasets, AI techniques employed, performance measures, findings, and practical implications. The extracted information was subsequently organized into two principal analytical themes: traditional valuation models and AI-based valuation techniques. Within each theme, additional subthemes were developed to facilitate systematic comparison, including theoretical foundations, data requirements, computational efficiency, predictive accuracy, transparency, interpretability, scalability, regulatory acceptance, and practical implementation in investment banking (9–13).

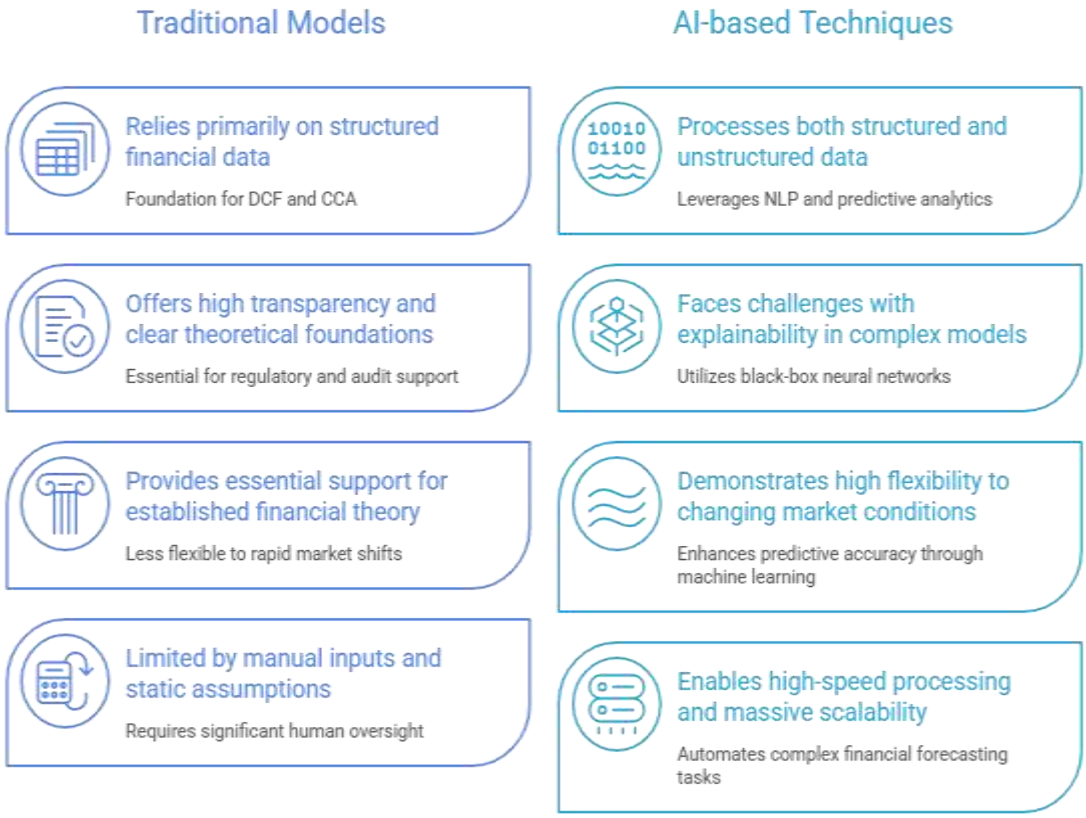

Figure 2. Comparison of Valuation Methods

A comparative analytical framework was then employed to evaluate the strengths and weaknesses of both valuation approaches across multiple dimensions. Particular emphasis was placed on comparing assumptions, flexibility, adaptability to changing market conditions, utilization of structured and unstructured data, computational capabilities, explainability, and decision-support potential. Rather than viewing AI and traditional valuation methods as competing alternatives, the analysis explored their complementary roles in supporting more accurate and informed investment decisions. This comparative approach enabled the identification of areas where AI enhances conventional valuation practices while highlighting situations in which traditional financial models continue to provide essential theoretical and regulatory support (14–18).

To enhance the credibility and reliability of the review, evidence was triangulated across multiple academic and professional sources, allowing consistent findings to be identified while minimizing individual study bias. Priority was given to highly cited research, recent publications, and studies appearing in reputable finance, economics, artificial intelligence, and information systems journals. Although the study does not involve primary data collection or statistical hypothesis testing, the systematic literature selection process, clearly defined evaluation criteria, and structured comparative analysis provide methodological rigor and ensure that the conclusions are grounded in reliable scholarly evidence. Consequently, the adopted methodology offers a comprehensive foundation for evaluating the evolving relationship between traditional valuation models and AI-driven valuation techniques and for assessing their future implications for investment banking practice (19–21).

Results and Discussion

The comparative analysis of the reviewed literature demonstrates that both traditional valuation models and AI-based valuation techniques possess distinct strengths and limitations, indicating that the future of investment banking is more likely to involve their integration rather than the replacement of one by the other. Traditional valuation approaches continue to provide the theoretical foundation for estimating intrinsic value, while AI technologies enhance analytical capabilities by processing vast quantities of financial and non-financial data with greater speed and precision. The findings consistently suggest that AI should be viewed as an enabling technology that complements conventional financial expertise instead of substituting professional judgment (1–3).

One of the most significant findings is that traditional valuation models remain indispensable because of their strong theoretical basis and widespread acceptance among investors, regulators, auditors, and financial institutions. Models such as Discounted Cash Flow (DCF), Comparable Company Analysis (CCA), Precedent Transaction Analysis (PTA), Dividend Discount Models (DDM), and Leveraged Buyout (LBO) analysis continue to dominate mergers and acquisitions, initial public offerings, corporate restructuring, and private equity transactions. Their popularity stems from their transparency, interpretability, and consistency with established financial theories. Decision-makers can clearly understand how assumptions regarding revenue growth, discount rates, terminal values, or comparable firms influence valuation outcomes, making these models particularly suitable for regulatory reporting and financial due diligence. However, the analysis also reveals that these methods are highly dependent on analyst assumptions and historical financial information, making them susceptible to forecasting errors during periods of economic uncertainty and rapid market change (4–6).

The literature further indicates that the effectiveness of traditional valuation techniques declines when businesses operate in highly dynamic industries characterized by technological disruption, intangible assets, digital business models, and rapidly changing competitive environments. Companies operating in artificial intelligence, biotechnology, fintech, or platform-based digital ecosystems often possess significant intangible resources that cannot be fully captured using conventional accounting information. Consequently, estimating future cash flows becomes increasingly difficult, while identifying appropriate comparable firms may also prove challenging. These limitations reduce the predictive capability of traditional valuation models, particularly for high-growth firms where historical financial performance is not an accurate indicator of future value creation (7,8).

In contrast, AI-based valuation techniques demonstrate superior performance in handling large, complex, and continuously evolving datasets. Machine learning algorithms such as Random Forests, Gradient Boosting Machines, Support Vector Machines, Artificial Neural Networks, and Extreme Gradient Boosting (XGBoost) have shown considerable potential in identifying nonlinear relationships among financial variables that are difficult to detect using traditional econometric approaches. Unlike conventional valuation models that rely on predetermined assumptions, AI algorithms continuously learn from historical observations and improve predictive accuracy as additional information becomes available. This adaptive capability enables AI systems to generate more responsive valuation estimates under volatile market conditions while reducing dependence on subjective analyst judgments (9–11).

Another important finding concerns the growing role of alternative data in corporate valuation. The reviewed studies consistently emphasize that AI systems can integrate structured financial information with unstructured datasets such as earnings-call transcripts, corporate disclosures, analyst reports, macroeconomic indicators, customer reviews, ESG disclosures, satellite imagery, web traffic statistics, and social media sentiment. Natural Language Processing (NLP) techniques further strengthen valuation by transforming qualitative textual information into measurable financial variables that improve prediction accuracy. This broader information base allows AI-driven valuation models to identify hidden market signals and emerging trends that traditional financial models frequently overlook. Consequently, investment banks adopting AI technologies gain access to richer information that supports more comprehensive valuation decisions (12–14).

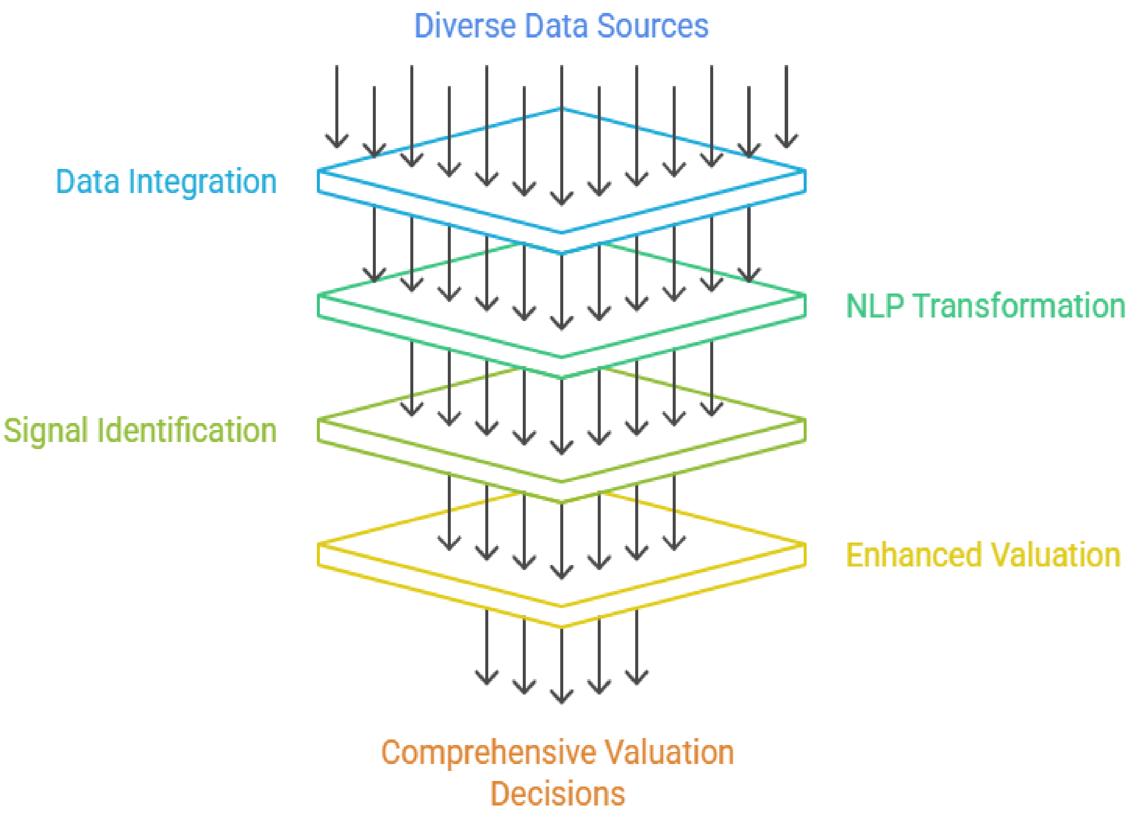

Figure 03. AI Driven Valuation Process

The findings also demonstrate that AI substantially improves operational efficiency within investment banking. Traditional financial modelling often requires extensive manual data collection, spreadsheet construction, sensitivity analysis, and report preparation, making the valuation process both time-consuming and resource-intensive. AI-based automation significantly reduces these repetitive activities by rapidly processing financial statements, extracting relevant information, generating financial forecasts, identifying valuation multiples, and producing preliminary analytical reports. More recently, generative AI and Large Language Models (LLMs) have begun supporting analysts in preparing investment memoranda, summarizing due diligence findings, generating scenario analyses, and assisting financial modelling. Such automation enables investment banking professionals to devote greater attention to strategic analysis, client interaction, negotiation, and complex decision-making rather than routine computational tasks (15).

Despite these advantages, the literature identifies several important limitations that constrain the widespread implementation of AI-based valuation techniques. One of the most frequently discussed concerns relates to model interpretability. Many advanced machine learning algorithms function as "black-box" systems, where the reasoning behind specific valuation outputs is not easily understood by analysts, auditors, regulators, or clients. Investment banking decisions frequently involve transactions worth billions of dollars, making transparency and accountability essential. Financial institutions therefore require valuation methodologies that can be explained, justified, and independently verified. Explainable Artificial Intelligence (XAI) has emerged as a promising solution by providing greater visibility into model behavior, feature importance, and prediction mechanisms; however, its practical implementation remains an evolving area of research (16,17).

Table 1. Limitations of AI-Based Valuation Techniques and Their Implications for Investment Banking.

Limitation	**Description**	**Impact on Investment Banking Valuation**	**Potential Solution**
Black-box nature of AI models	Advanced machine learning and deep learning models often produce valuation outputs without clearly explaining how predictions are generated.	Reduces transparency and makes it difficult for analysts, auditors, regulators, and clients to understand or validate valuation results.	Adoption of Explainable Artificial Intelligence (XAI) techniques to improve model interpretability.
Limited interpretability	Complex algorithms provide highly accurate predictions but offer limited insight into the contribution of individual variables.	Decreases stakeholder confidence and creates challenges in communicating valuation decisions to investors and regulatory authorities.	Use feature importance analysis, SHAP values, LIME, and interpretable machine learning models.
Regulatory compliance	Financial regulations require valuation methodologies to be transparent, auditable, and justifiable.	AI models that lack explainability may face regulatory scrutiny and limited acceptance in high-value financial transactions.	Develop AI governance frameworks and ensure compliance with regulatory standards.
Accountability and auditability	Determining responsibility for AI-generated valuation decisions is difficult when model logic is opaque.	Increases legal and operational risks during mergers, acquisitions, IPOs, and financial reporting.	Maintain human oversight and establish comprehensive AI audit trails.
Immature implementation of XAI	Although Explainable AI improves transparency, its application in financial valuation is still evolving.	Limits widespread adoption of AI-based valuation techniques in investment banking.	Continue research and integrate XAI with existing financial valuation frameworks.

Data quality represents another significant challenge affecting AI-based valuation. Machine learning algorithms depend heavily on large volumes of accurate, representative, and unbiased training data. Incomplete financial information, inconsistent accounting practices, missing observations, or biased datasets may substantially reduce model performance and produce unreliable valuation estimates. Furthermore, rapidly changing economic conditions, geopolitical events, financial crises, or unprecedented market disruptions may alter historical relationships among financial variables, thereby reducing the predictive capability of AI models trained on previous data. Consequently, continuous model monitoring, retraining, validation, and governance become essential components of successful AI implementation within investment banking (18).

The review further highlights several ethical and regulatory considerations associated with AI adoption. Financial institutions operate within highly regulated environments where transparency, fairness, data privacy, cybersecurity, and accountability are mandatory. AI systems may unintentionally introduce algorithmic bias if training datasets fail to represent diverse market conditions or company characteristics.

Similarly, increased reliance on proprietary algorithms raises concerns regarding regulatory oversight, auditability, and legal responsibility for automated investment decisions. These issues indicate that technological advancement alone cannot guarantee successful AI implementation; rather, robust governance frameworks, ethical guidelines, and regulatory compliance mechanisms must accompany AI deployment to maintain investor confidence and financial market integrity (19).

An important outcome of the comparative analysis is the recognition that human expertise remains indispensable despite rapid advances in AI technologies. Investment banking valuation extends beyond quantitative computation and requires consideration of strategic positioning, management quality, competitive dynamics, regulatory developments, geopolitical risks, organizational culture, and long-term industry trends. Many of these qualitative factors cannot yet be fully captured through algorithmic models. Experienced investment bankers contribute contextual understanding, negotiation skills, professional judgment, and ethical reasoning that complement AI-generated analytical outputs. Accordingly, the reviewed literature consistently supports a human-in-the-loop approach in which AI serves as an advanced decision-support system while final valuation decisions remain under expert supervision (20).

Table 2. Comparative Assessment of Human Expertise and AI in Investment Banking Valuation

Evaluation Criterion	**Human Expertise**	**AI-Based Techniques**	**Hybrid Approach (Human + AI)**
Quantitative data processing	3/5	5/5	5/5
Analysis of qualitative information	5/5	3/5	5/5
Decision-making speed	3/5	5/5	5/5
Pattern recognition	3/5	5/5	5/5
Strategic judgment	5/5	2/5	5/5
Adaptability to unforeseen events	5/5	3/5	5/5
Regulatory compliance	5/5	3/5	5/5
Explainability	5/5	2/5	4/5
Operational efficiency	3/5	5/5	5/5
Overall effectiveness	**4.0/5**	**3.8/5**	**4.9/5**

Scoring Scale: 1 = Very Low, 2 = Low, 3 = Moderate, 4 = High, 5 = Very High.

Overall, the findings strongly suggest that the future of investment banking lies in hybrid valuation frameworks that combine the theoretical robustness of traditional financial models with the computational intelligence of AI-based techniques. Traditional valuation methods continue to provide transparency, regulatory acceptance, and conceptual rigor, whereas AI contributes superior predictive capabilities, real-time analytics, automation, and integration of alternative data sources. Rather than competing technologies, these approaches represent complementary components of next-generation valuation systems. Investment banks that successfully integrate AI within established valuation frameworks are likely to achieve greater valuation accuracy, faster analytical processes, improved risk assessment, enhanced operational efficiency, and stronger strategic decision-making while preserving the accountability and professional judgment that remain fundamental to financial practice. As AI technologies continue to mature, their role will increasingly shift from automating routine analytical tasks to augmenting human expertise, ultimately transforming investment banking into a more data-driven, intelligent, and resilient industry capable of addressing the growing complexity of global financial markets (21).

Conclusion

The rapid advancement of Artificial Intelligence (AI) is fundamentally transforming the valuation landscape within the investment banking industry. This study compared traditional valuation models with emerging AI-based valuation techniques to examine their respective strengths, limitations, and future relevance. The review demonstrates that conventional approaches, including Discounted Cash Flow (DCF), Comparable Company Analysis (CCA), Precedent Transaction Analysis (PTA), Dividend Discount Models (DDM), and Leveraged Buyout (LBO) analysis, continue to provide a strong theoretical foundation for business valuation because of their transparency, interpretability, and widespread regulatory acceptance. However, these methods remain highly dependent on historical financial data, analyst assumptions, and static forecasting models, which may limit their effectiveness in increasingly volatile and data-intensive financial markets (1–7). In contrast, AI-based valuation techniques leverage machine learning, deep learning, natural language processing, predictive analytics, and generative AI to process large volumes of structured and unstructured data, identify complex nonlinear relationships, and generate more dynamic and timely valuation estimates. These capabilities improve forecasting accuracy, automate repetitive analytical tasks, and support faster decision-making in investment banking. Nevertheless, AI adoption is accompanied by challenges related to model interpretability, data quality, algorithmic bias, cybersecurity, and regulatory compliance, indicating that technological sophistication alone cannot replace professional expertise and sound financial judgment (8–17). Overall, the findings suggest that AI should not be viewed as a substitute for traditional valuation methodologies but rather as a complementary technology that enhances their effectiveness. The future of investment banking is therefore expected to be characterized by hybrid valuation frameworks that integrate established financial theories with advanced AI-driven analytical tools. Such an approach combines the transparency and credibility of conventional valuation models with the computational power and predictive capabilities of artificial intelligence, leading to improved valuation accuracy, operational efficiency, and strategic decision-making. Future research may focus on developing explainable AI models, integrating environmental, social, and governance (ESG) indicators into valuation frameworks, and evaluating the practical implementation of AI across different investment banking functions and global financial markets. These developments will contribute to building more intelligent, transparent, and resilient valuation systems capable of supporting sustainable financial decision-making in an increasingly digital economy (18–21). ..

REFERENCES

Ball, R., & Brown, P. (1968). Income numbers and share prices. Journal of Accounting Research, 6(2), 159–178. https://doi.org/10.2307/2490232

Beaver, W. H. (1968). The information content of annual earnings announcements. Journal of Accounting Research, 6, 67–92. https://doi.org/10.2307/2490070

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 23(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Ohlson, J. A. (1995). Earnings, book values, and dividends in equity valuation. Contemporary Accounting Research, 11(2), 661–687. https://doi.org/10.1111/j.1911-3846.1995.tb00461.x

Feltham, G. A., & Ohlson, J. A. (1995). Valuation and clean surplus accounting for operating and financial activities. Contemporary Accounting Research, 11(2), 689–731. https://doi.org/10.1111/j.1911-3846.1995.tb00462.x

Penman, S. H., & Sougiannis, T. (1998). A comparison of dividend, cash flow, and earnings approaches to equity valuation. Contemporary Accounting Research, 15(3), 343–383. https://doi.org/10.1111/j.1911-3846.1998.tb00564.x

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. The Journal of Finance, 59(3), 1259–1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance, 62(3), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. The Journal of Finance, 66(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Cecchini, M., Aytug, H., Koehler, G. J., & Pathak, P. (2010). Making words work: Using financial text as a predictor of financial events. Decision Support Systems, 50(1), 164–175. https://doi.org/10.1016/j.dss.2010.07.012

Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), 689–702. https://doi.org/10.1016/j.ejor.2016.10.031

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654–669. https://doi.org/10.1016/j.ejor.2017.11.054

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Sirignano, J., & Cont, R. (2019). Universal features of price formation in financial markets: Perspectives from deep learning. Quantitative Finance, 19(9), 1449–1459. https://doi.org/10.1080/14697688.2019.1622295

Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. PLOS ONE, 12(7), e0180944. https://doi.org/10.1371/journal.pone.0180944

Heaton, J. B., Polson, N. G., & Witte, J. H. (2017). Deep learning in finance. Annual Review of Financial Economics, 11, 145–181.

Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. Journal of Behavioral and Experimental Finance, 32, 100577. https://doi.org/10.1016/j.jbef.2021.100577 (ScienceDirect)

Wasserbacher, H., & Spindler, M. (2022). Machine learning for financial forecasting, planning and analysis: Recent developments and pitfalls. Digital Finance, 4, 63–88. https://doi.org/10.1007/s42521-021-00046-2 (Springer Link)

Long, Z., & Li, B. (2025). Agnostic fundamental analysis via machine learning. Accounting & Finance, 65, 2678–2700. https://doi.org/10.1111/acfi.70013 (Wiley Online Library)

Jensen, T. I., Kelly, B., Malamud, S., & Pedersen, L. H. (2026). Machine learning and the implementable efficient frontier. The Review of Financial Studies. https://doi.org/10.1093/rfs/hhag022 (OUP Academic)