STRUCTURED FINANCE ASSOCIATION

SFACADEMY'S

SFJOURNAL

Market Opinions

Written for Practitioners by Practitioners

Disclaimer:

The views and opinions expressed in this publication are those of the author(s) and do not necessarily reflect the views, positions, or policies of the Structured Finance Association (SFA).

STRUCTURED
FINANCE
ASSOCIATION

The Power of Universal LLM Data Ingestion to Build Generative AI-Powered Metadata

Bruno Lorenzelli – CEO of ExchangeRobotics
(Scalata Credit Platform), blorenzelli@exchangerobotics.com

Zivko Krstic – CTO of ExchangeRobotics
(Scalata Credit Platform) zkrstic@exchangerobotics.com

February 07, 2025

Abstract:

In this document the authors explore the transformative potential of Large Language Models (LLMs) in automating metadata generation within the financial sector, particularly in structured finance. The authors have extensive experience in building platforms using traditional methos of credit finance metadata and are the main promoters of a new method of using Generative AI to address new approaches. Traditional metadata creation methods struggle with the increasing scale and complexity of modern financial data, leading to inefficiencies and risks. LLMs offer a solution by providing a "universal" data ingestion capability, enabling efficient processing of diverse data sources and formats to generate high-quality, context-aware metadata. This automation enhances data discovery, improves risk management, streamlines compliance, and ultimately facilitates better decision-making. This document highlights specific use cases across various financial applications, including asset-backed securities (ABS), collateralized loan obligations (CLOs), residential and commercial mortgage-backed securities (RMBS & CMBS), synthetic risk transfer, and private credit. The findings suggest that LLM-powered metadata generation offers significant advantages in accuracy, efficiency, and scalability, paving the way for a more data-driven and robust financial industry. The paper concludes with the projection that the adoption of LLM technologies in finance is expected to grow substantially in the coming years, driving significant improvements in efficiency and effectiveness.

The effective management and utilization of data assets are crucial in today's data-driven world of finance; this is particularly relevant in credit finance. Metadata, or "data about data," plays a vital role in this process, enabling efficient data discovery, search, and analysis. However, traditional metadata creation methods struggle to cope with the scale and complexity of modern data. We have witnessed an explosion of data in the credit space fueled by the demand of credit solutions and new product, but more importantly by the demand of new liquidity solutions. The growth in the globalization of markets in the last 30 years has done nothing more than increase this phenomenon that today is out of control. This limitation creates inefficiencies and risks associated with poor data quality. LLMs present a transformative solution by automating metadata generation and empowering organizations to effectively manage their expanding data universe.

Similar to how market dynamics shifted during and following the 2008-2009 financial crisis, with an increasing awareness of risk and its associated pricing, today's environment also necessitates an evolution in data management practices. The growth of data and limitations of traditional methods echo the challenges faced during that period by investors dealing with illiquid markets and opaque pricing. LLM-powered metadata creation parallels the eventual rise of more sophisticated risk models and algorithmic trading strategies. Most, if not all, past attempts to establish standards for automating data management in the credit and structured finance industry have proven to be either poorly scalable and insecure on a global level, or to too costly to maintain in the long term.

The Struggle of Traditional Metadata Creation

The challenges of metadata creation mirror the pre-2008 financial crisis struggles in assessing financial risk. Historically, metadata creation relied heavily on manual processes or rule-based systems, similar to how early structured investment vehicles or collateralized debt obligations operated before proper regulatory oversight – both approaches faced inherent limitations that hindered scalability and risk management.

Managing data is fundamentally about managing standards in a complex workflow environment. In the credit industry, participants continuously exchange inputs and outputs in different data formats, which must be passed between internal and external counterparties. To address this, the Loan Level Initiative (LLI) was introduced by the European Central Bank in 2012, to standardize loan-level data reporting across Eurozone member states. Similarly, the Uniform Mortgage Data Program (UMDP) developed by Fannie Mae and Freddie Mac, under the guidance of the Federal Housing Finance Agency to standardize mortgage data. While the UMDP achieved greater success than the LLI due to strong regulatory backing, industry collaboration and clear implementation mandates both faced similar fundamental challenges: manual metadata creation remains inconsistent, costly, time-consuming, and prone to human error, while rule-based systems often struggle to accommodate the variability and structural nuances of real-world data sets.

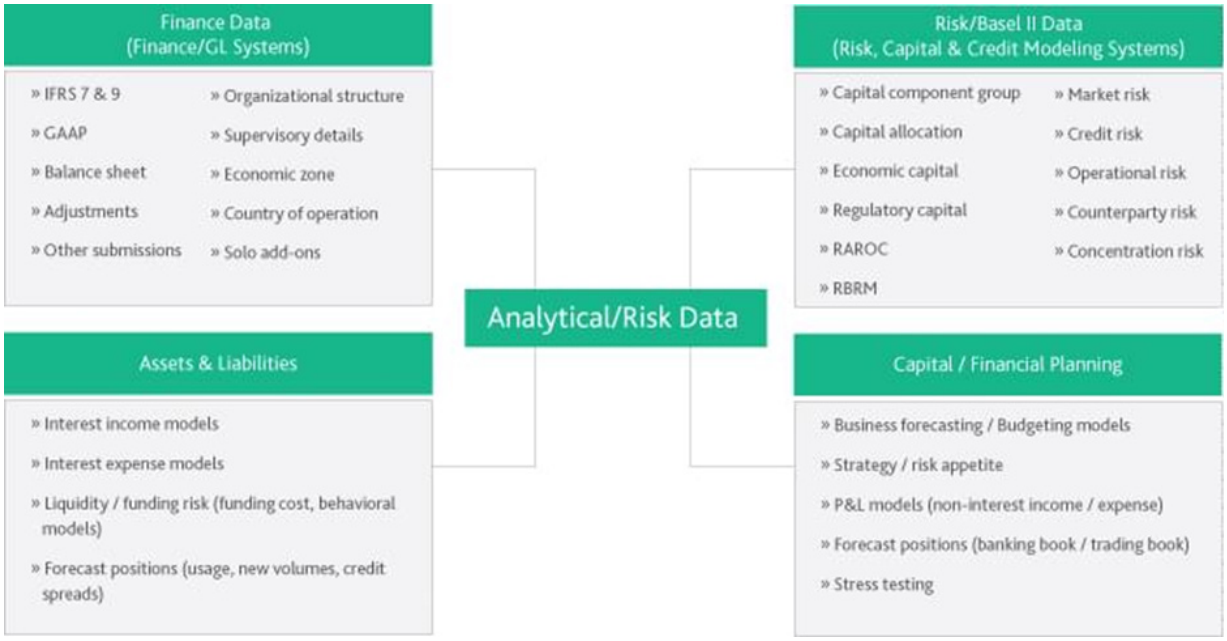
This inflexiblity mirrors the shortcomings of pre-crisis risk assessment models used by rating agencies, which relied heavily on standardized models that failed to capture the complexities and nuanced risks of novel structured finance products. These rigid models ultimately underestimated risk concentrations and eventually exposed the inherent weaknesses and risk concentrations in underlying asset pools, contributing to the financial crisis. Just as risk assessment practices evolved following the crisis, so too must metadata creation and application of robust metadata – adopting more adaptive, scalable, and automated approaches to meet the growing complexities of modern data ecosystems.

Traditional metadata creation relies heavily on manual processes or rule-based systems, both of which are time-consuming, expensive, and often inconsistent. Manual tagging is prone to human error and bias, while rule-based systems struggle to adapt to the nuances and complexities of real-world data, particularly in structured finance. The sheer volume and heterogeneous nature of data in the industry's data sets, encompassing loan-level details for RMBS and CMBS, collateral characteristics for ABS and CLOs, intricate deal structures for SRT, opacity of private credit, to name a few, exacerbates these issues. As noted, unstructured and unformatted data, costs the U.S. an estimated $3 trillion per year[1], and manual tagging failures are a significant contributor to this cost. These limitations hinder efficient data discovery, search, and analysis, impacting critical processes like due diligence, risk assessment, and regulatory reporting. Early AI and machine learning attempted to address these challenges but were often too domain-specific and lacked standardization (as discussed later), limiting their ability to address universal data ingestion and the metadata generation needs of the complex structured finance industry.

According to Moody's on the Foundation of Risk Management in Structured Finance, a core element of executing effective risk management is the proper organization of data. In particular this analysis specifically examines the link between regulatory adoption and the organization of data. Exhibit 1 demonstrate this in detail:

[1] https://hbr.org/2016/09/bad-data-costs-the-u-s-3-trillion-per-year

Exhibit 1. The Four Main Categories Of Analytical Data.



Source: Moody's, "Data: The Foundation of Risk Management"

The importance of adopting the proper model and secure technology to integrate and digest new data and new use cases can prove fundamental in the future existence of the fintech platform or investment made by any player, whether it is a financial institution or a startup or asset manager.

Past Approaches: A Landscape of Limitations

Before the widespread adoption of LLMs, several approaches were explored for automating metadata creation:

- ***Rule-based systems:*** Similar to how reliance on simplified rating models failed in finance, the rigid nature of rule-based systems lacked the adaptability necessary to deal with diverse data.
- ***Early AI and Machine Learning Attempts:*** Initial attempts, though conceptually similar to current LLMs, were like early attempts at portfolio diversification before widespread adoption of exchange-traded funds (ETFs): limited in scope, implementation, and efficiency.
- ***Specialized, Domain-Specific Solutions:*** Niche metadata tools resembled complex derivatives customized for specific market participants but lacked broad applicability across asset classes like standardized futures or options contracts. They couldn't effectively serve a global, inter-connected financial ecosystem.

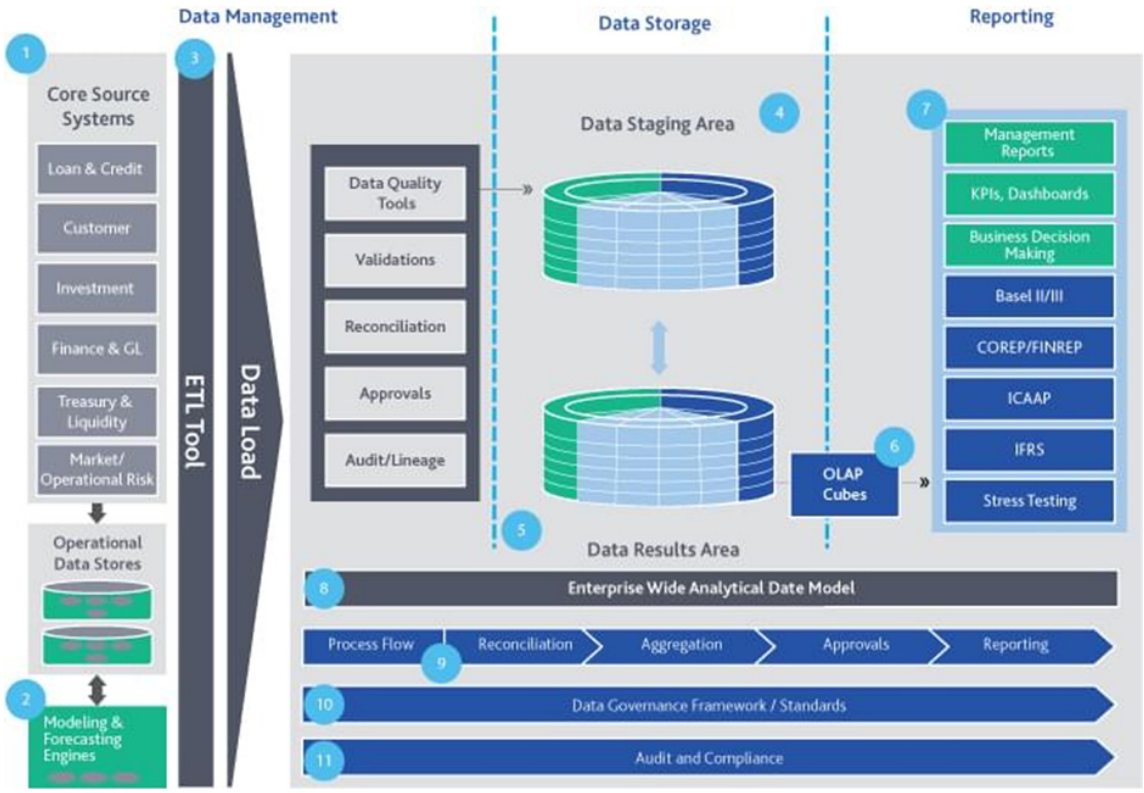
- ***Lack of Standardization and Interoperability:*** The metadata technology environment mirrored the fragmented and complex financial market structure pre-2008, where differing reporting standards and opaque regulations exacerbated instability during stress tests of global systemic stability. Interoperability was severely restricted just like the ability to conduct thorough due diligence across diverse securities, counterparties, and legal jurisdictions.

Several attempts have been made in the past ten years and prominent funding has flown into the research and development of new solutions able to support credit workflows. We are aware that most of the approaches by independently funded startups or internal banking projects have heavily prioritized standardizing the processes rather than leveraging technologies and strategies that align with the existing internal technology infrastructure and skill base of financial institutions.

The credit industry is uniquely affected globally by local processes, language barriers and stringent varying regulatory requirements that result in distinct workflows. As a result, the inherent struggle of these fintech platforms, both small or large per se, in dealing with metadata and data modelling, is the high maintenance costs of scaling and adapting the base infrastructure.

According to Moody's banks face seven key data and risk management problems in identifying key problems in data and risk management: 1) massive amounts of data in siloed legacy systems, making extraction and standardization difficult; 2) lack of a common data model hindering data aggregation; 3) reliance on slow, costly, and hard-to-audit manual data processes; 4) low-quality data due to input errors, unchecked changes, and aged data, exacerbated by multiple systems with no common data models and poor audit trails; 5) difficulty aggregating unstructured data (e.g., portfolios, derivatives) with structured data; 6) obtaining accurate, granular counterparty data for credit risk modeling, complicated by multiple sources and layers of guarantors and insurers; and 7) meeting regulatory compliance requiring accurate and secure data, full audit trails, and appropriate governance frameworks and IT platforms.

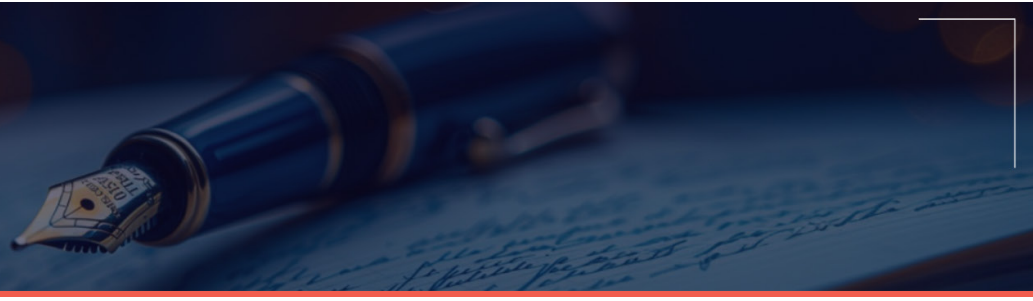
Exhibit 2. Data management and governance framework.



Source: Moody's, "Data: The Foundation of Risk Management

Universal LLM Data Ingestion and Generative AI

The power of LLMs lies in their ability to process vast amounts of diverse data. This "universal" ingestion capability allows LLMs to learn intricate patterns and relationships within data, far beyond the capacity of traditional rule-based systems. We explore how LLMs can be trained on diverse data sources, including structured data (databases), semi-structured data (XML, JSON), and unstructured data (text, images, audio). This capacity is crucial for the structured finance industry, which deals with numerous data sources and formats. For example, in the context of CMBS, LLMs can ingest and process data from various sources, including loan documents, property appraisals, and market data, to generate comprehensive metadata describing the underlying assets and the overall transaction. Similarly, in ABS, LLMs can handle the diversity of data related to different underlying assets. The "ai-and-fixed income" paper highlights the booming demand for data center ABS and CMBS driven by AI advancements, underscoring the need for efficient data management. The ability to handle both structured and unstructured data, as described in "generative-ai-help", is also critical for sectors like Private Credit, where extensive due diligence often involves reviewing qualitative information alongside financial statements.

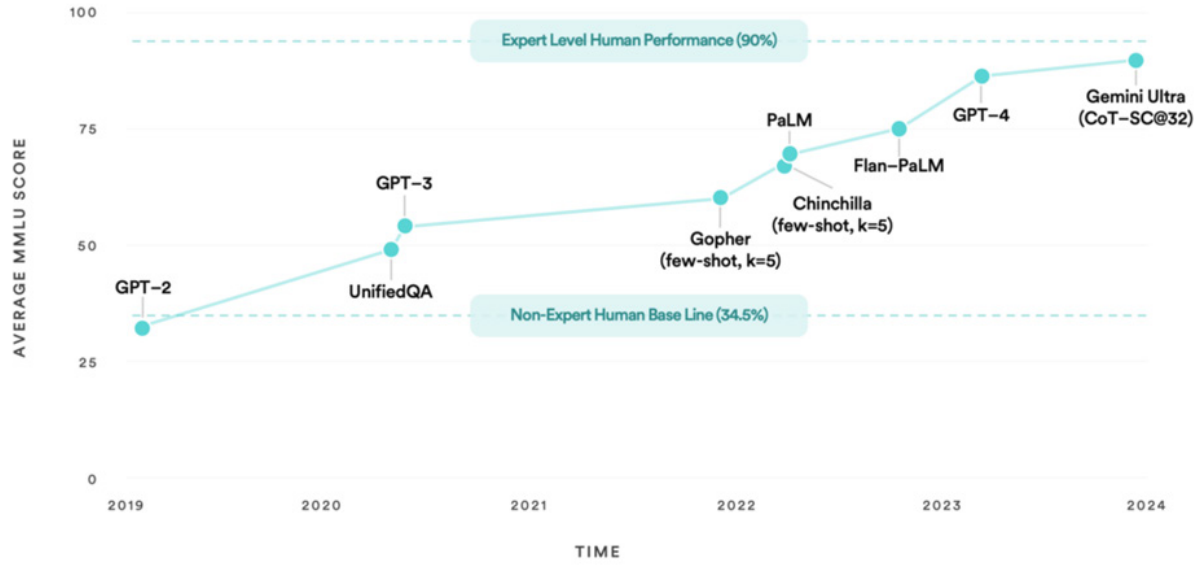


LLMs, specifically the transformer-based architecture found in models like GPT, Gemini or Claude, overcome limitations of prior metadata solutions. The universal data ingestion capacity of LLMs allows for effective pattern recognition and inference among multiple and diverse data types from simple relational database outputs, various file formats, unstructured textual outputs, media rich datasets including still imagery and video/audio media. Key functionalities enabling such efficiency gains are listed below.

- ***Fine-tuning:*** This process refines the LLMs generalized contextual awareness with granular knowledge related to a specified task – analogous to portfolio optimization where investment allocation weights are assigned dynamically based on forward looking capital market and interest rate assumptions for expected risk premia across diverse asset classes in both developed and emerging markets
- ***Transfer Learning:*** This empowers LLMs to adapt quickly, applying their contextual awareness across diverse, novel use-cases in a streamlined fashion; the financial equivalent of utilizing arbitrage strategies across geographically disparate but ultimately functionally connected market centers, exploiting perceived inconsistencies between relative risk premia of highly correlated investment portfolios by executing complex trades based on the relative timing and location of market transactions clearing in centralized electronic clearing houses.

These technical advantages underpin metadata capabilities including the production of detailed descriptors/ tags which describe datasets from their core structure to granular subcomponents via text based and numeric features/ classifications. Beyond descriptive properties, LLM generative AI approaches produce summarization content as well and more recently can output inferences in terms of quality assurance in various dataset formats across multiple industry contexts spanning scientific and business and legal applications – the LLM generated outputs have also achieved superior discoverability compared with prior technology in managing highly sensitive Personal Identifiable Information (PII) via the secure training paradigm within encrypted execution sandboxed from external networked connected endpoints or data stores.

Exhibit 3: Average MMLU (massive multitask language understanding) score over time

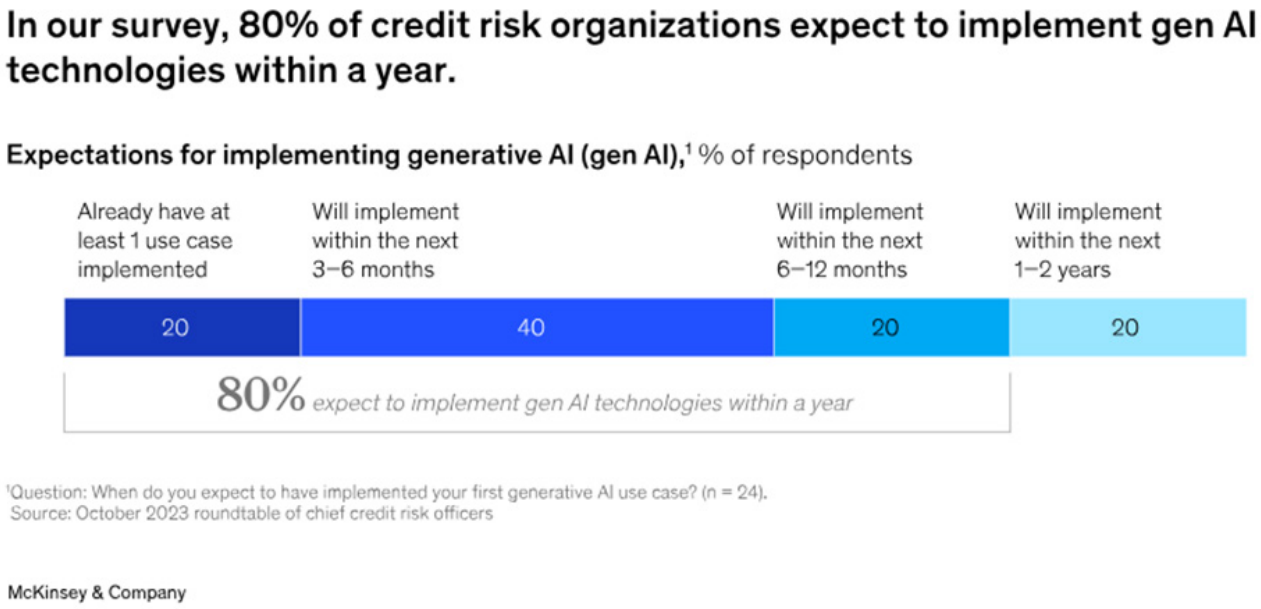


Source: Foundation Capital, "Why 2024 Will Be the Year of Inference," Foundation Capital, n.d.,

Similar to the importance of regulation and increased transparency following the 2008-2009 financial crisis, these technical functionalities enable fine-tuning metadata outcomes by sector domain; increased auditability of outputs by the transparent log trail across the process end-to-end, improving workflow quality and reducing error rates; and scalability to handle data and storage demands by utilizing elastic infrastructure from modern cloud providers to conduct highly distributed concurrent data transformation, analysis, processing, summarization, descriptive content tagging.

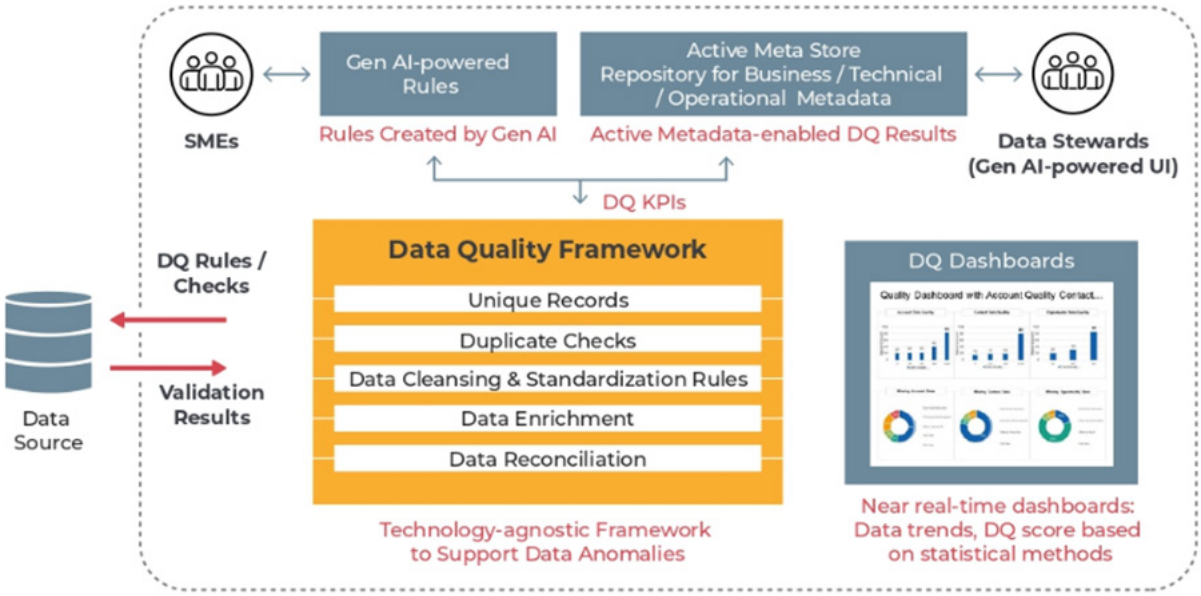
According to a recent article by McKinsey & Company, "Embracing Generative AI in Credit Risk", generative AI is rapidly being adopted by financial institutions for credit risk management. McKinsey & Company cites the execution of a survey where they found that many institutions are already using or plan to use generative AI within the next two years. Applications span the credit lifecycle, from client engagement to portfolio monitoring, leveraging large language models to analyze data and automate tasks. Current uses are primarily focused on internal operations, such as pre-populating climate risk questionnaires and drafting credit memos, resulting in significant time savings. However, scaling these applications presents challenges, including risk management, talent shortages, and defining clear use cases. To fully realize generative AI's potential, institutions need a comprehensive strategy encompassing a roadmap, aligned processes, robust technology, and a strong governance model. While full implementation will take time, even partial adoption can yield substantial improvements in efficiency and effectiveness.

Exhibit 4: Expectations for implementing generative AI



Source: McKinsey & Company, "Embracing Generative AI in Credit Risk"

Exhibit 5: Improving data quality with Generative AI



Source: WNS"Generative AI: A Catalyst for Data-Driven Growth," WNS, n.d., February 7

Generative AI can significantly improve efficiency in structured finance by automating key workflows. AI-powered data extraction can process loan agreements, financial statements, and regulatory documents, reducing manual effort. Risk assessment models can analyze historical data, perform stress tests, and generate predictive insights to enhance decision-making. Automated document summarization helps financial professionals quickly extract key insights from lengthy reports and legal documents. Compliance monitoring is streamlined through AI-driven regulatory checks that cross-reference financial data with legal requirements. Portfolio monitoring becomes more efficient with AI-generated analytics, risk alerts, and trend predictions in real time. Investor and stakeholder communications can be automated by generating reports, presentations, and market insights tailored to specific audiences. AI-driven workflow optimization enables faster approvals and intelligent prioritization of tasks to enhance operational efficiency. Integrating Generative AI with existing financial systems ensures seamless data flow and automation across structured finance processes. By implementing these AI-driven solutions, structured finance teams can achieve faster decision-making, reduced errors, and a scalable approach to managing complex financial instruments.

Generative AI can significantly improve efficiency in structured finance by automating key workflows. AI-powered data extraction can process loan agreements, financial statements, and regulatory documents, reducing manual effort. Risk assessment models can analyze historical data, perform stress tests, and generate predictive insights to enhance decision-making. Automated document summarization helps financial professionals quickly extract key insights from lengthy reports and legal documents. Compliance monitoring is streamlined through AI-driven regulatory checks that cross-reference financial data with legal requirements. Portfolio monitoring becomes more efficient with AI-generated analytics, risk alerts, and trend predictions in real time. Investor and stakeholder communications can be automated by generating reports, presentations, and market insights tailored to specific audiences. AI-driven workflow optimization enables faster approvals and intelligent prioritization of tasks to enhance operational efficiency. Integrating Generative AI with existing financial systems ensures seamless data flow and automation across structured finance processes. By implementing these AI-driven solutions, structured finance teams can achieve faster decision-making, reduced errors, and a scalable approach to managing complex financial instruments.

Benefits and Use Cases

Once trained on diverse data, LLMs can generate high-quality, context-aware metadata automatically. This involves leveraging the LLM's understanding of language and semantics to extract key information and generate descriptive tags, summaries, and other metadata elements. The process moves beyond simple keyword extraction to encompass a deeper understanding of the data's content and context. In the context of Synthetic Risk Transfer, LLMs can help analyze complex legal documentation and extract key terms related to risk transfer mechanisms and obligations. The automation of metadata generation improves efficiency and reduces the potential for human error, as discussed in the "IJMIE paper," particularly relevant for time-sensitive processes in structured finance. The "RI_Risks_generative" paper emphasizes the potential for generative AI to improve efficiency in various financial applications, directly translating to the structured finance domain. [should include citations to these papers]

- **Data Complexity and Transparency:** LLMs address the industry's challenge of managing large volumes of complex data, from loan-level data in RMBS to complex deal structures in SRT, by automating metadata creation and improving data quality. Furthermore, techniques to enhance LLM explainability (as emphasized in the KPMG document) can be implemented to address the need for transparency in credit decisions, critical for satisfying regulatory scrutiny and investor demands.
- **Market Volatility and Risk Management:** LLMs can significantly improve risk assessment and stress testing, especially in volatile markets. By generating synthetic data and simulating diverse scenarios, LLMs enhance the accuracy and comprehensiveness of stress tests for structured products, as highlighted in the IJMIE document. They can also be used to improve portfolio optimization strategies by modeling complex risk transfer transactions, crucial for managing exposures in volatile market conditions.
- **Specific Asset Class Applications:** LLMs can be tailored for different asset classes within structured finance:
    - **ABS & CLO:** Automate extraction of collateral data, waterfall provisions, and other key details from deal documents, streamlining due diligence and improving transparency.
    - **RMBS & CMBS:** Analyze loan-level data, property valuations (as described in the T. Rowe Price, "AI and Fixed Income: Booming Demand for Data Center ABS and CMBS," T. Rowe Price, 2024, February 7, 2025), and macroeconomic indicators to improve risk identification, predict defaults, and refine pricing models, especially crucial in the non-agency space.
    - **Synthetic Risk Transfer:** Facilitate more efficient modeling of complex risk transfer structures and assess the effectiveness of various hedging strategies.

- **Private Credit:** Automate data extraction from often unstructured sources like private company financials and legal documents, improving deal origination, underwriting, and portfolio monitoring.

LLM-powered metadata generation offers numerous advantages over traditional approaches:

- ***Enhanced Accuracy and Consistency:*** Just like using sophisticated risk models reduced valuation uncertainties and mismatches on corporate balance sheets prior to the financial crisis, LLMs reduce metadata inaccuracies and inconsistencies.
- ***Increased Efficiency and Scalability:*** Like automated trading platforms enabling market makers to facilitate liquidity efficiently across a multitude of electronic exchanges, LLMs enhance the speed and scale of metadata processing.
- ***Improved Discoverability:*** LLMs generate richer metadata and enhance data discoverability, much like how better corporate governance and disclosure standards enable equity market participants to make well informed asset allocation decisions without incurring undue operational risk.

Specific Use Cases in Financial Services

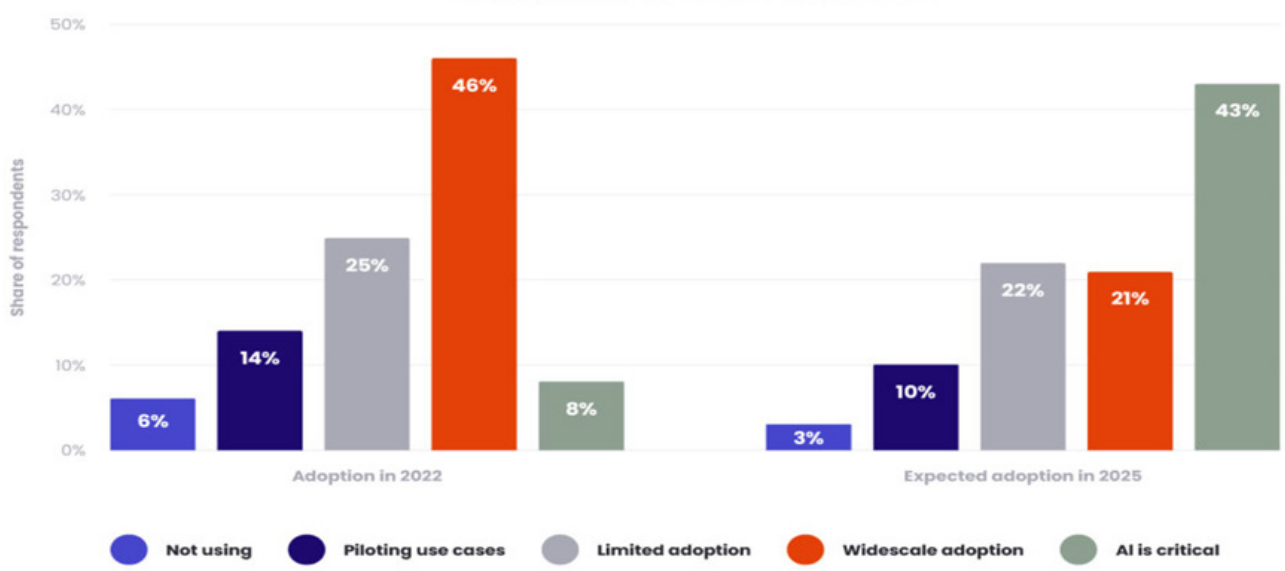
Just as new market practices (more transparency, higher capitalization requirements) benefited sub-sectors differently following 2009, the various aspects of LLM enhancements similarly differentiate outcomes in the verticals enumerated below across multiple key operational dimensions and capabilities as shown

- ***Asset Management & Hedge Funds:*** Improving portfolio analysis, risk assessment, and reporting similar to enhancements in quantitative analysis methods, enabling higher fidelity modelling capabilities for diverse multi-factor portfolio construction methodologies (value investing, alpha premia capturing based on smart beta metrics or via arbitrage of correlated strategies), reducing overall exposure while maximizing risk-adjusted gains for end client stakeholders, enabling dynamic risk monitoring across diverse asset classes, echoing post-crisis counterparty analysis procedures
- ***Fund Administration:*** Automating critical calculations (NAV, IRR), and reporting, enabling transparency similar to central clearing practices which ultimately benefit investors and overall system wide stability
- ***Mortgage Lenders:*** Restructuring workflows in loan processing with advanced analytics to further reduce risk
- ***Private Credit:*** Automating deal terms, communications, and risk reporting – the modern-day equivalent of more robust covenant frameworks enforced upon corporate borrowing obligors following financial downturns. Improved monitoring and risk metrics similarly enable deal term recalibration with counterparty involvement by automating many aspects via secure dealroom solutions in cloud services.

Conclusion and Future Directions

The use of LLMs for metadata generation represents a significant advancement in data management. The benefits of improved accuracy, efficiency, and scalability are substantial. Further research is needed to address potential biases, improve explainability and transparency of LLM-generated metadata, and ensure fairness. Security and privacy implications also require careful consideration, especially when dealing with sensitive financial data. The adoption of LLMs for metadata generation is poised to significantly change how organizations manage and utilize data in structured finance. The shift towards LLM-powered metadata creation mirrors the post-crisis transformation in finance towards more data-driven decision making, enhanced monitoring and controls, and more frequent risk assessments to account for tail event scenarios in both systemic global downturns and in hyperlocalized shocks impacting multiple but disconnected participants. As a result, overall market behavior has become more resilient, decreasing severity and duration of localized volatility episodes.

Exhibit 6: AI adoption rate in financial businesses worldwide (2022-2025)



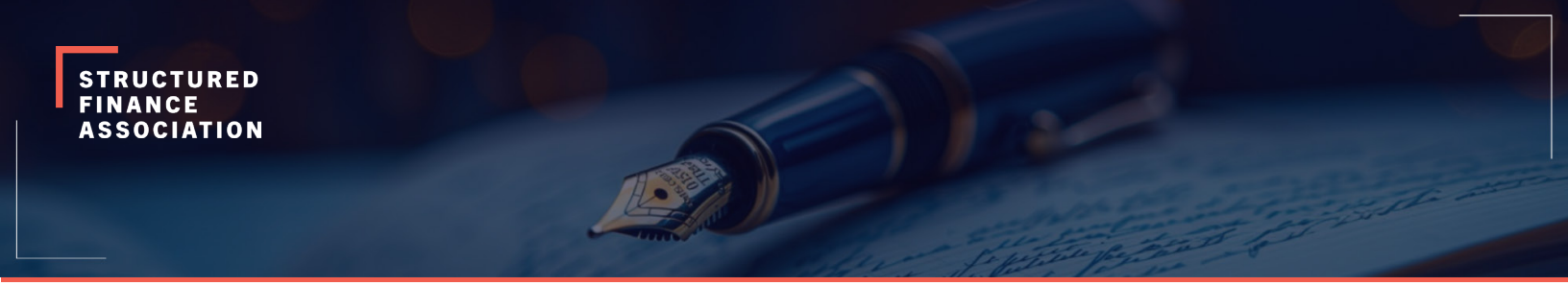
Source: Statista, 2024

Future developments will focus on improving model transparency – much like how rating models came under regulatory scrutinized post-crisis– while also addressing biases and refining more adaptive LLM structures – all mirroring the post-crisis financial evolution. LLM integration with broader data management systems echoes the financial industry's broader trend of integrating new risk management strategies within finance departments across firms at banks, brokers, and all manner of buyside investment vehicles. Just as enhanced analytic tools provided deeper insight post-2009 enabling portfolio diversification, optimized capital allocation, and precise valuations across new instruments and global markets, LLMs too will provide higher fidelity insights, generate new sources of alpha across ever larger complex heterogeneous pools of structured assets, and help mitigate embedded liquidity risk that are inherent in legacy structured credit markets.

References:

- Moody's, "Data: The Foundation of Risk Management," Moody's, n.d., February 7, 2025. https://www.moodys.com/web/en/us/insights/banking/data-the-foundation-of-risk-management.html
- Moolchandani, Sanjay. "The Integration of Generative AI in Credit Risk Management." Journal Homepage: http://www. ijmra. us 14, no. 02 (2024).
- CaseWare, "Problems with Manual Data Entry and How to Avoid Them," CaseWare Blog, February 7, 2025. https://www.caseware.com/resources/blog/problems-manual-data-entry-avoid/
- Redman, Thomas C. "Bad data costs the US $3 trillion per year." Harvard Business Review 22 (2016): 11-18. https://dataladder.com/wp-content/uploads/2019/07/Bad-Data-Costs-the-U.S-3-Trillion-Per-Year.pdf
- Park, Jung-ran, and Yuji Tosaka. "Metadata creation practices in digital repositories and collections: Schemata, selection criteria, and interoperability." Information Technology and Libraries 29, no. 3 (2010): 104-116. https://ital.corejournals.org/index.php/ital/article/download/3136/2750
- T. Rowe Price, "AI and Fixed Income: Booming Demand for Data Center ABS and CMBS," T. Rowe Price, 2024, February 7, 2025. https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.troweprice.com/financial-intermediary/us/en/insights/articles/2024/q3/ai-and-fixed-income-booming-demand-for-data-center-abs-and-cmbs.html&ved=2ahUKEwjk_YX8nLKLAxUPyAIHHcxuHC4QFnoECBIQAQ&usg=AOvVaw19i-Qzj4Lb6mxDBfD2dNJW
- Roosevelt Institute, Risks of Generative AI for Financial Services Brief (September 2024), accessed February 7, 2025. https://rooseveltinstitute.org/wp-content/uploads/2024/09/RI_Risks-Generative-AI-Financial-Services_Brief_202409.pdf
- KPMG, Generative AI Helps Banks Accelerate Digital Transformation (2024), accessed February 7, 2025. https://kpmg.com/us/en/articles/2024/generative-ai-help-banks-accelerate-digital-transformation.html
- McKinsey & Company, "Embracing Generative AI in Credit Risk", McKinsey & Company, n.d., February 7, 2025. https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/embracing-generative-ai-in-credit-risk
- Foundation Capital, "Why 2024 Will Be the Year of Inference," Foundation Capital, n.d., February 7, 2025. https://foundationcapital.com/why-2024-will-be-the-year-of-inference/

- MarketsandMarkets, “Large Language Model (LLM) Market,” MarketsandMarkets, n.d., February 7, 2025. https://www.marketsandmarkets.com/Market-Reports/large-language-model-llm-market-102137956.html
- WNS, “Generative AI: A Catalyst for Data-Driven Growth,” WNS, n.d., February 7, 2025. https://www.wns.com/perspectives/articles/articledetail/1121/generative-ai-a-catalyst-for-data-driven-growth
- Statista, “AI Function Adoption Rates for Business Finance,” Statista, n.d., February 7, 2025, https://www.statista.com/statistics/1346736/ai-function-adoption-rates-business-finance/.com/statistics/1346736/ai-function-adoption-rates-business-finance/.



We invite submissions from industry experts and academics alike. If you have research that offers fresh insights and practical implications, we want to hear from you. Manuscripts should be between 2,500 and 3,500 words, excluding abstracts and references, and must be original work that has not been previously published or is under consideration elsewhere.

In line with our commitment to integrity and transparency, any use of AI tools in your manuscript should be limited to mechanical tasks like editing or citation management, with full disclosure required. Our strict guidelines ensure that only high-quality, relevant, and ethically produced research is featured in the journal.

Submissions must adhere to the *Chicago Manual of Style* (CMS) for formatting, with specific requirements for typography and content organization. We encourage authors to carefully structure their work, starting with a clear and concise title and abstract, followed by a compelling introduction, organized headings, and a well-rounded conclusion. Exhibits should be properly sourced, and permissions obtained for any previously published material. Details may be found on our online submissions platform.

Join us in advancing the structured finance industry by sharing your expertise and research. Submit your manuscript today and contribute to the growing body of knowledge that SFJ proudly supports. Please contact Elen Callahan at elen.callahan@structuredfinance.org with your questions and interest.

Structured Finance Journal Masthead

Managing Editor
Elen Callahan, *Head of Research and Education*, **SFA**

Editorial Board

Mark Adelson, *Independent Consultant*
William Black, *Founder and Principal,* **Black Analytics**
Nicole Byrns, *Founder and Principal*, **Dumar Capital**
Chun Lin, *Managing Director and Head of U.S. Residential Mortgage Modeling*, **Bank of America**
Debra Lofano, *Partner*, **Alston & Bird LLP**
Phillip Millman, *Advisor*, **Federal Housing Finance Agency**
Tim O'Neil, *Managing Director and Head of Canadian Structured Finance*, **Morningstar DBRS**
David Reiss, *Clinical Professor of Law & Research Director of the Blassberg-Rice Center for Entrepreneurship Law,* **Cornell Law School & Cornell Tech**
Jeff Schwartz, *CFA*, *Securitized Products Investor*

Junior Editors

Caleb Adebayo, *Associate*, **AO Shearman**
Ace Pawlikowski, *Managing Associate*, **Dentons Capital Markets**

Senior Advisor

Gary Zhu, *Senior Vice President and Deputy Chief Investment Officer of Insurance*, **Alliance Bernstein**

Special Advisory Council

Matt Bisanz, *Partner*, **Mayer Brown LLP**
Caroline Chen, *Senior Research Analyst*, **Allspring Global Investments**
Kayvan Darouian, *Director,* **Deutsche Bank Research**
Dorothy Giobbe, *Counsel,* **Alston & Bird LLP**
Selma Hepp, *Senior Vice President and Chief Economist*, **CoreLogic**
Frank Vetrano, *CFA*
Vadim Verkhoglyad, *Vice President and Head of Research and Publications*, **dv01**
Joy Zhang, *Managing Director*, **MSCI**