Slide 1: Title Slide

Good [morning/afternoon], everyone. Today I?ll be presenting a study titled 'From Man vs. Machine to Man + Machine: The Art and AI of Stock Analyses'. This work explores how artificial intelligence performs in the world of equity forecasting ? and more importantly, whether collaboration between humans and machines yields better outcomes than competition alone.

Slide 2: A Moment in History: Man vs. Machine

Let?s start with a familiar moment. In 1997, Garry Kasparov ? the reigning world chess champion ? lost to IBM?s Deep Blue. It wasn?t just a game of chess. It symbolized the growing power of machine intelligence and the anxiety it provoked about human obsolescence.

Slide 3: From Adversaries to Allies

But what followed was unexpected. Kasparov didn?t walk away from the game ? instead, he reimagined it. He introduced 'centaur chess,' where a human works alongside a machine. The result? These human-machine hybrids often outperformed both traditional grandmasters and standalone computers. This idea ? that man and machine could collaborate, not just compete ? is central to the study I?m about to share.

Slide 4: From Chess to Finance

Inspired by this centaur concept, the authors of this paper asked: Can the same logic apply to stock analysts? Could an AI model compete with, or even complement, professional human forecasters in the world of finance? To test this, they created an AI analyst and compared its predictions against those of real human analysts.

Slide 5: Meet the Analysts

In this study, we?re not comparing abstract systems. We?re comparing two types of forecasters: the traditional human analyst, and the AI analyst. Human analysts bring experience, context, and often access to information that?s not in the data. But they?re also prone to biases and inconsistencies. The AI analyst, on the other hand, is systematic and data-driven ? capable of processing huge volumes of information without fatigue, but often blind to nuance.

Slide 6: The Prediction Setup

Both the AI and human analysts are asked to predict stock returns 12 months ahead. These predictions are based on target prices, not earnings. Target prices offer a clearer view of an analyst?s valuation belief, and are less likely to be distorted by short-term incentives or managerial manipulation.

Slide 7: Research Questions

The study focuses on three core research questions: First, can AI outperform human analysts in forecasting returns? Second, in what contexts do human analysts retain an advantage? And third, can a hybrid approach ? combining AI and human forecasts ? produce better outcomes than either one alone?

Slide 8: Methodology: Overview

The authors build an AI analyst using machine learning. For each forecast date, the model is trained on a rolling 3-year window of prior data ? just like a human analyst using recent history. Importantly, the model uses only public data and does not rely on analyst forecasts.

Slide 9: Methodology: Modeling Approach

The AI analyst is an ensemble of three model types. LSTM networks capture time-series patterns. Random forests handle a wide range of structured features and interactions. Gradient boosting focuses on refining predictions through successive learning. The ensemble combines their strengths for a more robust forecast.

Slide 10: The Data: Sample Overview

The data spans over 1.15 million analyst forecasts between 2001 and 2018. It covers thousands of U.S. firms across sectors and sizes. The AI model is built using structured data from I/B/E/S, Compustat, and CRSP, as well as text and sentiment data from RavenPack, Twitter, SEC filings, and patent databases.

Slide 11: The Data: AI Analyst Input Overview

The AI analyst uses only publicly available information ? including fundamentals, market performance, sentiment, and textual analysis. For each prediction, it?s trained using the previous 3 years of data ? simulating real-time decision-making without look-ahead bias.

Slide 12: The Data: Categories of Inputs

These inputs are grouped into six categories: firm-level data, industry context, macroeconomic variables, corporate filings, news and social media sentiment, and innovation indicators like patent value. This range reflects the full landscape a skilled analyst would consider.

Slide 13: The Data: Structured Inputs

Structured data includes financial ratios, size, returns, volatility, and liquidity measures. Industry-level variables account for competition and sector dynamics. Macroeconomic inputs capture broad conditions like inflation, interest rates, and market sentiment.

Slide 14: The Data: Textual and Alternative Inputs

Textual inputs come from 10-K, 10-Q, and 8-K filings, using sentiment dictionaries and readability metrics. News sentiment is captured through RavenPack, and firm-level social media sentiment is drawn from Twitter. Patent value provides a signal for innovation.

Slide 15: Results: Performance ? AI vs. Human

When predictions are compared, the AI analyst outperforms the best human analyst in about 54.5% of cases. This is based on squared forecast error, measured over a long time horizon. Importantly, this is achieved using only public data ? no private access or inside information.

Slide 16: Results: When Humans Outperform AI

But humans still hold an edge in specific scenarios. These include firms with high intangibles, distressed financials, and illiquid stocks. These situations call for soft judgment, institutional knowledge, and sometimes information that?s not in the data.

Slide 17: Results: Man + Machine ? The Hybrid Model

What if we combine both? The authors test a hybrid model that incorporates both AI forecasts and analyst inputs. The result? Slightly better accuracy ? and more importantly, significantly fewer big mistakes.

Slide 18: The Hybrid Model Avoids Extreme Errors

The hybrid model avoids 90.7% of the largest forecast errors made by human analysts, and 43.6% of the errors made by AI. This matters. In finance, extreme errors can be costly. Reducing those outliers improves real-world reliability.

Slide 19: Conclusion

So what did we learn? First, yes ? AI can outperform human analysts in a majority of cases. Second, humans still matter in complex or ambiguous settings. And third, the most effective approach is not choosing one over the other ? but combining them. From man vs. machine to man + machine ? the future of stock analysis is collaborative.