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From Reactive to Anticipatory: Agentic AI Systems for Pre-Emptive Risk Detection in Volatile Power Sector Stocks

Diptimayee Dash[1], Kirankumar Balagi[2]

[1,2]School of Management Studies & Research, KLE Technological University, Hubballi, India

Abstract:
The financial markets, particularly India's power sector, are increasingly susceptible to multi-layered risks arising from regulatory shifts, geopolitical tensions, commodity price volatility, and policy reversals. Traditional reactive investment strategies which respond to risk only after it manifests in price have proven inadequate for protecting retail and institutional investors alike. This study introduces the concept of Agentic Artificial Intelligence (Agentic AI) as a paradigm shift from reactive to anticipatory risk management in stock investment decision-making. Drawing on a primary survey of 200 individual investors across India with exposure to NSE-listed power sector stocks (Adani Power, Tata Power, NHPC, and NTPC), this research develops and validates a six-construct Structural Equation Model (SEM) examining the interplay between Awareness of Agentic AI (AA), Perceived Anticipatory Capability (PAC), Perceived Risk Reduction (PRR), Trust in Agentic AI (TAI), Behavioral Intention to Adopt (BI), and Investment Decision Confidence (IDC). Findings reveal that PAC significantly mediates the relationship between AI awareness and investor trust, and that trust is the most powerful predictor of adoption intention. Furthermore, IDC is confirmed as a downstream outcome of adoption readiness. The paper contributes a theoretically grounded, empirically validated framework for deploying Agentic AI in volatile stock environments and offers practical implications for fintech developers, SEBI regulators, and investor education programmes.

Keywords: Agentic AI, power sector stocks, pre-emptive risk detection, structural equation modelling, investor behaviour, Impact of fintech in India.

1. Introduction

Investing in the stock market has never been a passive activity. It demands constant vigilance, quick judgement, and an ability to read subtle signals before they escalate into significant financial losses. For Indian retail investors, particularly those with exposure to the power sector, this challenge is compounded by the sector's inherent sensitivity to government policy, fuel cost dynamics, environmental regulations, and geopolitical events affecting energy imports.

Consider a scenario that played out repeatedly between 2022 and 2024: a sudden change in coal import duty, a revision in renewable energy purchase obligations, or a Supreme Court order on mining rights could send a listed power stock tumbling 8 to 12% in a single session. Investors who acted only after the news broke the reactive majority absorbed the worst of the damage. Those who had advance signals fared measurably better.

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This study is motivated by a simple but powerful question: what if artificial intelligence could detect these risk signals before they move the market? Not in the science-fiction sense of infallible prediction, but in the practical sense of continuous, autonomous surveillance of hundreds of data streams regulatory filings, commodity futures, news feeds, parliamentary debates, pollution board orders — and alerting investors to building risk concentrations before they crystallise into price shocks.

This is precisely what Agentic AI promises. Unlike conventional AI tools that respond only when prompted, agentic systems operate autonomously, pursuing defined goals (in this case, risk surveillance), taking multi-step reasoning actions, and updating their assessment continuously. The financial literature has documented the predictive power of machine learning in equity markets (Gu et al., 2020; Lopez de Prado, 2018), but the specific application of agentic, autonomous, goal-directed AI for pre-emptive risk detection in sectoral equities remains underexplored.

This paper fills that gap. We present a conceptual framework grounded in Technology Acceptance Model (TAM) and Trust-based Adoption frameworks, test it empirically through a structured survey of 200 power-sector investors, and validate it using Structural Equation Modelling (SEM). Our findings carry implications for investors, fintech product designers, and financial market regulators.

2. Literature Review

2.1 From Algorithmic Trading to Agentic AI

The evolution of AI in financial markets has passed through three broad phases. The first, spanning the 1980s and 1990s, involved rule-based algorithmic trading: systems executing pre-defined if-then strategies at machine speed. The second phase, beginning in the early 2010s, brought machine learning to finance models that learned patterns from data to forecast prices, detect fraud, or optimise portfolios (Dixon et al., 2020). The third and current phase involves large language model (LLM)-powered agents capable of reasoning, planning, and taking autonomous multi-step actions (Wang et al., 2024).

Agentic AI distinguishes itself from earlier paradigms through four characteristics: goal-directedness (it pursues an objective autonomously), tool use (it can call APIs, browse data, read filings), memory (it retains context across interactions), and multi-agent coordination (specialised agents can collaborate to complete complex tasks). In financial risk surveillance, this translates to systems that can simultaneously monitor regulatory news, commodity prices, social media sentiment, and historical price patterns without requiring human prompting between each step.

2.2 Risk Detection in Power Sector Stocks

The Indian power sector presents a compelling case for advanced risk surveillance. Studies by Gupta and Mehrotra (2021) documented that power stocks on NSE exhibit above-average volatility during monsoon cycles, budget announcements, and fuel price revisions. Kumar et al. (2022) found that renewable energy policy announcements affect not only renewable-focused utilities but create ripple effects across coal-based producers such as Adani Power and NTPC through shifting merit-order dispatch.

Traditional risk management in equity investing relies heavily on reactive indicators: stop-loss orders, trailing averages, or beta-adjusted exposure limits. These tools, while useful, are fundamentally backward-looking. They react to risk after it has already manifested as price movement. The literature on early-warning systems (EWS) in banking (Lo Duca & Peltonen, 2013) offers a parallel: EWS models that identify macroprudential vulnerabilities before crises occur. Translating EWS logic to equity markets through agentic AI represents a novel and timely contribution.

2.3 Technology Acceptance and Investor Behaviour

The Technology Acceptance Model (Davis, 1989) posits that perceived usefulness and perceived ease of use determine technology adoption intent. Subsequent extensions TAM2 (Venkatesh & Davis, 2000), UTAUT (Venkatesh et al., 2003), and trust-augmented TAM (Gefen et al., 2003) have incorporated social influence, facilitating conditions, and trust as additional determinants.

In financial technology specifically, trust has emerged as the dominant adoption barrier. Shen et al. (2021) found that explainability of AI recommendations significantly moderates trust formation among retail investors. Cao et al. (2022) demonstrated that investors with prior positive experience of robo-advisory tools exhibit significantly higher adoption readiness for autonomous AI systems. Our study extends this line of inquiry to the specific context of agentic risk-detection AI and tests a mediated model in which anticipatory capability perceptions bridge awareness and trust.

2.4 Research Gap

While individual threads exist in the literature AI in trading, power sector risk analysis, fintech adoption behaviour no study has synthesised these into an empirically validated model of how agentic AI can serve as a pre-emptive risk surveillance tool for power sector investors, or examined the psychological and behavioural pathways through which investors come to trust and adopt such systems. This paper addresses that gap.

3. Conceptual Framework and Hypotheses

3.1 Research Framework

Our model proposes that investor exposure to agentic AI tools and information (Awareness of Agentic AI, AA) shapes their beliefs about the system's ability to anticipate risk (Perceived Anticipatory Capability, PAC). This belief directly and indirectly (through Trust in Agentic AI, TAI) shapes Behavioral Intention to Adopt (BI), which ultimately enhances Investment Decision Confidence (IDC). Perceived Risk Reduction (PRR) operates as a parallel pathway, mediating the relationship between anticipatory capability beliefs and trust formation.

Construct	Code	Definition
Awareness of Agentic AI	AA	Investor's knowledge and familiarity with autonomous AI tools for stock monitoring
Perceived Anticipatory Capability	PAC	Belief that agentic AI can detect risk signals before they impact stock prices
Perceived Risk Reduction	PRR	Expectation that agentic AI will reduce portfolio losses from sudden volatility
Trust in Agentic AI	TAI	Confidence in the reliability, accuracy, and transparency of agentic AI risk alerts
Behavioral Intention to Adopt	BI	Willingness to use agentic AI tools for power sector investment monitoring

Construct	Code	Definition
Investment Decision Confidence	IDC	Enhanced confidence in timing and quality of investment decisions via AI support

Table 1: Research Constructs and Operational Definitions

3.2 Hypotheses

Based on the theoretical grounding above, we propose the following hypotheses:

- H1: Awareness of Agentic AI (AA) positively influences Perceived Anticipatory Capability (PAC).
- H2: Perceived Anticipatory Capability (PAC) positively influences Perceived Risk Reduction (PRR).
- H3: Perceived Risk Reduction (PRR) positively influences Trust in Agentic AI (TAI).
- H4: Perceived Anticipatory Capability (PAC) positively influences Trust in Agentic AI (TAI) directly.
- H5: Trust in Agentic AI (TAI) positively influences Behavioral Intention to Adopt (BI).
- H6: Behavioral Intention to Adopt (BI) positively influences Investment Decision Confidence (IDC).
- H7: PRR mediates the relationship between PAC and TAI.

4. Research Methodology

4.1 Research Design

This study adopts a quantitative, cross-sectional survey design. A structured questionnaire was developed based on the six constructs of the proposed model, with items adapted from established scales in the technology acceptance and investor behaviour literature. The questionnaire underwent expert review by three faculty members in finance and AI, followed by a pilot test with 30 respondents to assess clarity and item reliability before the main data collection.

4.2 Sample and Data Collection

The target population comprised individual investors in India who hold or have traded power sector stocks listed on the NSE within the past three years. Purposive and snowball sampling techniques were employed to reach this specific investor group through online investment forums, brokerage platform communities, and university alumni networks in finance.

A total of 230 questionnaires were distributed. After removing responses with incomplete data (n = 18) and straight-line response patterns indicating disengagement (n = 12), the final usable sample comprised 200 respondents. This sample size is consistent with recommended thresholds for SEM analysis (Hair et al., 2019), which suggest a minimum of 5 observations per estimated parameter, and our model's 28 indicators and 6 latent constructs require a minimum of approximately 140 to170 responses.

4.3 Measurement Instrument

The questionnaire comprised seven sections: Section A captured demographic variables (age, gender, occupation, investment experience, stock exposure, investment volume). Sections B through G contained Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) measuring the six constructs: AA (4 items), PAC (5 items), PRR (4 items), TAI (4 items), BI (4 items), and IDC (4 items), yielding 25 scale items in total.

4.4 Analytical Approach

Data analysis followed a two-stage SEM approach (Anderson & Gerbing, 1988). First, Confirmatory Factor Analysis (CFA) was conducted using AMOS 26.0 to assess the measurement model for reliability and validity. Second, the structural model was estimated to test the proposed hypotheses. Mediation analysis for H7 followed the bootstrapping procedure which recommended by Preacher and Hayes (2008). Additionally, Pearson correlation analysis and multiple regression were conducted as supplementary checks to confirm directional relationships.

5. Research Questionnaire

Instructions: Please rate your level of agreement with the following statements on a 5-point scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Section A: Demographic Profile

#	Question	Response Options
A1	Age group	Below 25 / 25–35 / 36–45 / 46–55 / Above 55
A2	Gender	Male / Female / Prefer not to say
A3	Occupation	Salaried / Self-employed / Professional Investor / Student / Retired
A4	Investment experience	< 1 year / 1–3 years / 3–5 years / > 5 years
A5	Do you invest in power sector stocks (Adani Power, Tata Power, NHPC, NTPC)?	Yes / No
A6	Monthly equity investment amount	< ₹5,000 / ₹5,000–20,000 / ₹20,000–50,000 / > ₹50,000

Section B: Awareness of Agentic AI (AA)

Code	Item	Scale
AA1	I am aware of AI tools that can autonomously monitor stock market data without human intervention.	1–5
AA2	I understand the difference between traditional algorithmic trading and agentic AI systems.	1–5
AA3	I have used or interacted with AI-based investment tools or robo-advisors.	1–5
AA4	I actively follow developments in AI applications for financial markets.	1–5

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Section C: Perceived Anticipatory Capability (PAC)

Code	Item	Scale
PAC1	Agentic AI can identify early warning signals of risk before they significantly impact stock prices.	1–5
PAC2	Such systems can detect regulatory, geopolitical, or commodity-related risks affecting power stocks in advance.	1–5
PAC3	Agentic AI can simultaneously monitor multiple risk factors (news, policy changes, fuel prices) in real time.	1–5
PAC4	AI-driven anticipatory alerts would help me act before a major price movement occurs.	1–5
PAC5	Agentic AI is more capable than human analysts in detecting subtle pre-crisis patterns in power stocks.	1–5

Section D: Perceived Risk Reduction (PRR)

Code	Item	Scale
PRR1	Using agentic AI for risk detection would reduce my potential investment losses in power sector stocks.	1–5
PRR2	Agentic AI helps in better timing of entry and exit decisions during volatile market periods.	1–5
PRR3	I feel more confident managing portfolio risk when supported by agentic AI early-warning alerts.	1–5
PRR4	Agentic AI reduces the financial impact of sudden market shocks on my power sector holdings.	1–5

Section E: Trust in Agentic AI (TAI)

Code	Item	Scale
TAI1	I trust the accuracy of risk predictions made by agentic AI systems for power sector stocks.	1–5
TAI2	I am comfortable allowing AI systems to autonomously flag risk signals in my investment portfolio.	1–5
TAI3	I believe agentic AI systems are transparent about how they arrive at risk-related decisions.	1–5
TAI4	I would trust agentic AI more if its reasoning were explainable and its decisions were auditable.	1–5

Section F: Behavioral Intention to Adopt (BI)

Code	Item	Scale
BI1	I intend to use agentic AI tools for monitoring my power sector stock investments in the near future.	1–5
BI2	I would recommend agentic AI-based risk detection tools to fellow investors in my network.	1–5
BI3	I am willing to pay a reasonable subscription fee for an agentic AI risk monitoring service.	1–5
BI4	I plan to increase my reliance on AI-driven tools for investment decisions over the next 2–3 years.	1–5

Section G: Investment Decision Confidence (IDC)

Code	Item	Scale
IDC1	My confidence in making timely investment decisions improves when supported by AI-based anticipatory insights.	1–5
IDC2	I feel less anxious about power sector volatility when using agentic AI risk alerts.	1–5
IDC3	Agentic AI helps me reduce emotional or impulsive decision-making during volatile periods.	1–5
IDC4	Overall, agentic AI enhances the quality of my investment decisions in the power sector.	1–5

6. Results

6.1 Demographic Profile of Respondents

The final sample of 200 respondents skewed moderately toward the 25 to 45 age group (61.5%), reflecting the demographic most active in equity markets in India. Male respondents constituted 67% of the sample, with female investors accounting for 30% and the remainder preferring not to disclose gender. Approximately 58% were salaried professionals, and 22% identified as self-employed or business owners. Over 64% had investment experience exceeding three years, and 71% confirmed active holding of at least one of the four target power stocks (Adani Power, Tata Power, NHPC, or NTPC). Monthly equity investment amounts were distributed across categories, with the largest cluster (38%) investing between ₹5,000 and ₹20,000 per month.

Demographic Variable	Category	Frequency	Percentage (%)
Age	Below 25	28	14.0
	25–35	72	36.0
	36–45	51	25.5
	46–55	34	17.0
	Above 55	15	7.5
Gender	Male	134	67.0
	Female	60	30.0
	Prefer not to say	6	3.0
Investment Experience	Less than 1 year	18	9.0
	1–3 years	54	27.0
	3–5 years	76	38.0
	More than 5 years	52	26.0
Power Stock Investor	Yes	142	71.0
	No	58	29.0

Table 2: Demographic Profile of Respondents (N = 200)

6.2 Descriptive Statistics and Correlations

Descriptive statistics revealed that respondents expressed moderate-to-high awareness of AI investment tools (AA Mean = 3.42, SD = 0.81) and strong beliefs in AI's anticipatory capability (PAC Mean = 3.87, SD = 0.74). Trust levels were moderate on average (TAI Mean = 3.31, SD = 0.88), reflecting the documented trust gap in AI-driven financial decision support. Intention to adopt was higher than trust, suggesting that perceived utility precedes full trust formation in this domain (BI Mean = 3.68, SD = 0.79). Investment decision confidence showed the highest mean (IDC Mean = 3.91, SD = 0.72), suggesting respondents strongly associated AI support with improved decision quality.

Construct	Mean	SD	AA	PAC	PRR	TAI	BI	IDC
AA	3.42	0.81	1.00					
PAC	3.87	0.74	0.54**	1.00				
PRR	3.65	0.78	0.47**	0.61**	1.00			

Construct	Mean	SD	AA	PAC	PRR	TAI	BI	IDC
TAI	3.31	0.88	0.42**	0.58**	0.63**	1.00		
BI	3.68	0.79	0.39**	0.52**	0.55**	0.71**	1.00	
IDC	3.91	0.72	0.35**	0.49**	0.51**	0.64**	0.74**	1.00

*Table 3: Descriptive Statistics and Pearson Correlation Matrix (** p < 0.01)*

6.3 Measurement Model — Confirmatory Factor Analysis

CFA results confirmed acceptable model fit: $\chi^2/df = 2.14$, CFI = 0.963, TLI = 0.957, RMSEA = 0.049, SRMR = 0.052. All factor loadings exceeded 0.60, with the majority above 0.70, confirming convergent validity. Composite Reliability (CR) values ranged from 0.81 to 0.91 across constructs, exceeding the 0.70 threshold. Average Variance Extracted (AVE) values ranged from 0.54 to 0.68, all above the 0.50 threshold (Fornell & Larcker, 1981). Discriminant validity was confirmed as the square root of each construct's AVE exceeded inter-construct correlations.

Construct	Items	Factor Loading Range	CR	AVE	Model Fit
AA	4	0.62–0.79	0.83	0.55	$\chi^2/df = 2.14$
PAC	5	0.68–0.84	0.89	0.62	CFI = 0.963
PRR	4	0.71–0.83	0.87	0.63	TLI = 0.957
TAI	4	0.65–0.88	0.91	0.68	RMSEA = 0.049
BI	4	0.70–0.85	0.88	0.64	SRMR = 0.052
IDC	4	0.72–0.87	0.89	0.65	

Table 4: Measurement Model — CFA Results

6.4 Structural Model and Hypothesis Testing

The structural model was estimated using maximum likelihood estimation. All hypothesised paths were statistically significant at $p < 0.01$. Trust (TAI) emerged as the strongest predictor of adoption intention ($\beta = 0.68$, $p < 0.001$), and adoption intention strongly predicted investment decision confidence ($\beta = 0.71$, $p < 0.001$). Perceived anticipatory capability demonstrated both a direct effect on trust (H4: $\beta = 0.41$) and an indirect effect through perceived risk reduction (H2→H3: indirect $\beta = 0.29$), confirming partial mediation by PRR.

Hypothesis	Path	β	SE	t-value	p-value	Decision
H1	AA → PAC	0.54	0.06	9.21	< 0.001	Supported

Hypothesis	Path	β	SE	t-value	p-value	Decision
H2	PAC → PRR	0.61	0.07	8.74	< 0.001	Supported
H3	PRR → TAI	0.48	0.08	6.12	< 0.001	Supported
H4	PAC → TAI (direct)	0.41	0.07	5.88	< 0.001	Supported
H5	TAI → BI	0.68	0.06	11.33	< 0.001	Supported
H6	BI → IDC	0.71	0.05	14.20	< 0.001	Supported
H7	PAC → PRR → TAI (mediation)	0.29	0.05	5.43	< 0.001	Supported

Table 5: Structural Model Results — Hypothesis Testing

6.5 Mediation Analysis

Bootstrap mediation analysis (5,000 resamples, 95% bias-corrected CI) confirmed that PRR partially mediates the PAC→TAI relationship. The indirect effect was $\beta = 0.29$ (95% CI: [0.18, 0.41]), with the direct path remaining significant ($\beta = 0.41$, $p < 0.001$), confirming partial rather than full mediation. This suggests that while risk reduction perception is an important pathway through which anticipatory capability builds trust, a meaningful direct cognitive appraisal route also exists.

7. Discussion

7.1 Trust as the Central Pivot

The most striking finding of this study is the centrality of trust in the adoption pathway. With a path coefficient of 0.68, TAI was the strongest predictor of BI more powerful than even the belief that AI could reduce risk. This aligns with the broader fintech literature (Shen et al., 2021) but takes on particular resonance in the power sector context, where a wrong AI signal could precipitate significant financial loss on a high-volatility stock.

What does this mean practically? It suggests that fintech developers should not lead with capability claims (performance, accuracy, speed) but with transparency mechanisms: explainable alerts, historical track records, and human-in-the-loop override options that reassure investors that they retain ultimate control even as the AI monitors autonomously.

7.2 The Anticipatory Capability Pathway

The confirmation of H1 (AA→PAC) and H4 (PAC→TAI) reveals an important educational dynamic: investors who understand what agentic AI can do specifically its ability to detect regulatory, geopolitical, and commodity risks before they move prices develop higher trust in the technology. This suggests that awareness campaigns and investor education programmes should specifically communicate the mechanism of anticipatory detection, not just the fact that AI can 'analyse markets'.

7.3 The Mediating Role of Risk Reduction Perception

The PRR mediation finding (H7) adds nuance: belief in AI's anticipatory capability translates partly into trust through the instrumental perception that the technology will concretely reduce losses. This is a rational, outcome-focused pathway. Investors are not solely responding to the intellectual appeal of AI sophistication; they need to believe it will protect their money. Product design implications are clear: risk reduction scenarios, backtested performance evidence, and counterfactual demonstrations ('what would have happened if you had this alert three months ago?') should be central to any agentic AI investment tool.

7.4 Implications for Indian Power Sector Investors

For investors specifically exposed to Adani Power, Tata Power, NHPC, and NTPC, the relevance of pre-emptive risk detection is acute. These stocks face a particularly complex risk matrix: coal import dependency, renewable transition timelines, hydropower seasonal cycles, and regulatory frameworks governed by multiple bodies (CERC, MoP, SEBI, state electricity commissions). An agentic AI system that autonomously monitors this multi-dimensional risk landscape and alerts investors before price impact represents genuine value addition that conventional stock screeners and technical analysis tools do not provide.

8. Conclusion

This paper set out to explore whether, and how, agentic AI could shift the investment experience from reactive crisis management to anticipatory risk governance in the context of India's volatile power sector stocks. The answer, supported by empirical data from 200 investors and validated through Structural Equation Modelling, is a qualified but compelling yes.

Agentic AI holds genuine promise as a pre-emptive risk detection tool. Investors who understand its capabilities develop meaningful trust in it, and that trust drives strong adoption intention and, ultimately, greater investment decision confidence. The key battleground is trust, and the key to building trust is combining demonstrated anticipatory capability with radical transparency about how the AI reaches its conclusions.

For regulators at SEBI, the findings suggest that a framework for certifying and auditing agentic AI advisory tools along the lines of robo-advisory guidelines but extended to cover autonomous multi-step agents would accelerate responsible adoption. For fintech developers, the message is clear: build for explainability first, capability second. For educators and investors, the challenge is awareness: the more investors understand how these systems work, the more likely they are to adopt them in ways that genuinely enhance their financial outcomes.

Future research should extend this framework to other sectoral equities (banking, infrastructure, pharmaceuticals), examine longitudinal adoption patterns, and test the model's generalisability across emerging markets beyond India.

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