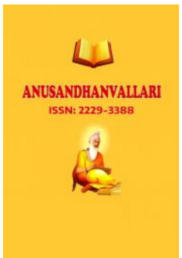

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AI-Driven Dividend Signaling Theory: A Conceptual Framework for Computational Corporate Finance

Anbumalar S[1], Avanthika M[2]

[1]Research Supervisor & Assistant Professor, Department of Commerce,

Sri Krishna Arts and Science College,

B K Pudur, Sugunapuram East, Kuniamuthur, Coimbatore, TN, India.

anbumalars@skasc.ac.in

[2]Ph.D Research Scholar, Department of Commerce,

Sri Krishna Arts and Science College,

B K Pudur, Sugunapuram East, Kuniamuthur, Coimbatore, TN, India.

Email ID: avanthi.m.17@gmail.com

ORCID ID: 0000-0001-8058-439X

Abstract

Purpose: The paper attempts to develop a new theoretical model of AI-Driven Dividend Signaling Theory for understanding the integration of artificial intelligence technology into the classical signaling theory in providing significantly effective corporate payout decisions. The paper helps to explore the theoretical gap between traditional theory and algorithmic corporate finance.

Design/Methodology/Approach: Using a theoretical modeling approach, the study combines the classical signaling theory with artificial intelligence in decision-making processes through mathematical representations. This exhibits how machine learning techniques work on data variability dynamics, signaling expenses, and market analysis methods.

Findings: Three signaling levels are identified, namely, improved data processing, dynamic signal optimization, and computational market engagement from the theoretical framework where traditional signaling approaches and market interpretation transform at each level.

Originality/Value: This paper is an introductory theoretical model intended for the AI-driven dividend policy in algorithmic corporate finance and also proposes testable hypotheses for further experiential studies.

Keywords: Artificial Intelligence, Dividend Signaling Theory, Algorithmic Corporate Finance, Information Disparity, Machine Learning

JEL Classification: G35, G32, G14, C78

1. Introduction

Predictive modeling and neural network technology are advancing day-by-day into different horizons, bringing innovative development in health science, technology, management science, finance, etc., Artificial intelligence is widely used in various areas, but it is still in the developing stage in most of the countries. Corporate finance explains the vital role financing, investing, and dividend decisions play in the company's future. The behavioral pattern of the investor has an influential role in the market disparity of a company, which led to the development of efficient market theory (EMT). There are evident applications of artificial intelligence in areas such as stock trading, portfolio building, and risk management, but the integration of AI into business and financial decisions is still unexplored, establishing a significant research gap in the literature (Yi et al., 2023). The utilization of artificial intelligent technology and machine learning in understanding the market conditions and applying it in business decisions can significantly help in the advancement of the business in the rapidly evolving world. The existing literature of Bhattacharya (1979) and Miller & Rock (1985) on traditional dividend signaling theory on the human-made managerial decisions appears to be outdated when considered in an AI-driven context (Taleb, 2019). The study explains the need for advanced modification of algorithms affecting dividend decisions with consideration of key hypotheses such as data disparity (Myers & Majluf, 1984), signaling costs (JOHN & WILLIAMS, 1985), and market analysis (Allen et al., 2000). AI is largely used in companies to gather and analyze information from various sources in making decisions in complex situations and enhancing economic growth (Lehner et al., 2022). But still, there are enough theoretical gaps that are to be explored in the current industrial scenario. This area has significant scope in the future for dividend decision-making. The reports of McKinsey (2023) find that in 2030, firms incorporating AI in their business can expect a rise of up to 12% in the profits, whereas PwC (2024) suggests that the world economy can make up to $15.7 trillion by 2030 with AI's improving capability. Thus, this paper explains the theoretical scope of how AI-Driven Dividend Signaling Theory, combining the traditional frameworks and artificial intelligence, helps in taking better dividend decisions. This framework can be validated further for future empirical research in the advancing algorithmic corporate finance area.

2. Review of Literature and Theoretical Development

2.1 Classical Dividend Signaling Theory

The dividend notion was initially explored by Miller and Modigliani, who found that business worth in perfect market conditions has no impact on dividend decisions, leading to the irrelevance argument in 1961. But considering the fact that the market cannot always be perfect, Bhattacharya (1979) argued that dividend policy has a significant signaling effect on market conditions, as the dividend announcements communicate the undisclosed information on the future cash flow of the company (Taleb, 2019). Taxation and other financial tensions cause potential costs on dividends, which signals realistically that low-performing firms cannot viably imitate the dividend policy like high-performing firms (Bhattacharya, 1979). The managerial operations have a vital influence on the company's growth, and when market data disparity is considered, dividend payout becomes the major signal of the company's future prospects (Khang & King, 2005; Taleb, 2019). Therefore, it is considered the indicator of stable performance of a company by market experts and policymakers (Ayunku & Richard Apiri, 2020). Later, subsequent studies on signaling processes (Ambarish et al., 1987; Bernheim & Wantz, 1995), clientele effects (Elton & Gruber, 1970; Scholz, 1992), and agency concerns (Easterbrook, 1984; Jensen, 1986) were explored. Recently, the literature showed a significant advancement in behavioral finance to enhance the understanding about the dividend policy of the companies, the correlation between dividend distributions and corporate performance, considering their impact on shareholder value and dynamic signaling models. But there is no current theoretical model covering the use of AI in dividend decision-making.

2.2 AI and Financial Decision Making

There is a notable upsurge in the application of artificial intelligence in financial decision making especially in the area of algorithmic trading, risk management and customer assistance. AI was first used in the area of finance for automation of trading, risk analysis etc. through instruction-based systems which were inferior compared to AI capabilities in present scenario (Quinn, 2023) AI has largely enriched the precision and pace of analyzing varied datasets in detecting malicious transactions, and complex relationship between financial information across banking, insurance, and healthcare sectors (Patil, n.d.; Prabin Adhikari et al., 2024). Algorithmic trading and predictive modeling are one such area of AI integration, where the vast real-time market information are processed and analyzed in higher pace, and portfolio are constructed at optimal level, which is not humanly possible (Buchanan, n.d.). Chatbots and virtual assistants helps the customer in resolving the issues and queries by providing instant support. But, research on application of AI in dividend decision-making is still at the exploratory stage, offering scope for future empirical research on how optimal corporate dividend policy can be employed with AI augmentation.

2.3 Theoretical Gap and Framework Development

Even though there is remarkable advancement in the use of artificial intelligence in the financial markets, there is an evident research gap in the application of AI in dividend signaling theory. Traditional dividend signaling theory explains the role of dividend payout in communicating the firm's growth prospect to its investor by decreasing the data discrepancy. But it does not interpret the ability that AI holds in enhancing the accuracy and efficiency in decision-making. This existing theory appears to be outdated when it comes to analyzing and incorporating huge volumes of information, resulting in a need for upgrading. This is the place where incorporation of AI could be beneficial. In the integration of AI in finance, the organizational norms and rules play an influential role. Assumptions of classical signaling theory, that is, data asymmetry, signaling expenses, and market information, may appear to be not practically possible, so that can be improvised with the capability of AI in processing data, cost cutting, and market transformation with the help of careful assessment. The AI-Driven Dividend Signaling Theory helps in gathering and analyzing large amounts of financial information and interpreting their complex relationships at high speed and accuracy; optimal payout policy can be achieved by decoding and forecasting the real-time market conditions with AI-driven algorithms, and automation of dividend announcements enhances lower information delay by strengthening the dividend signals.

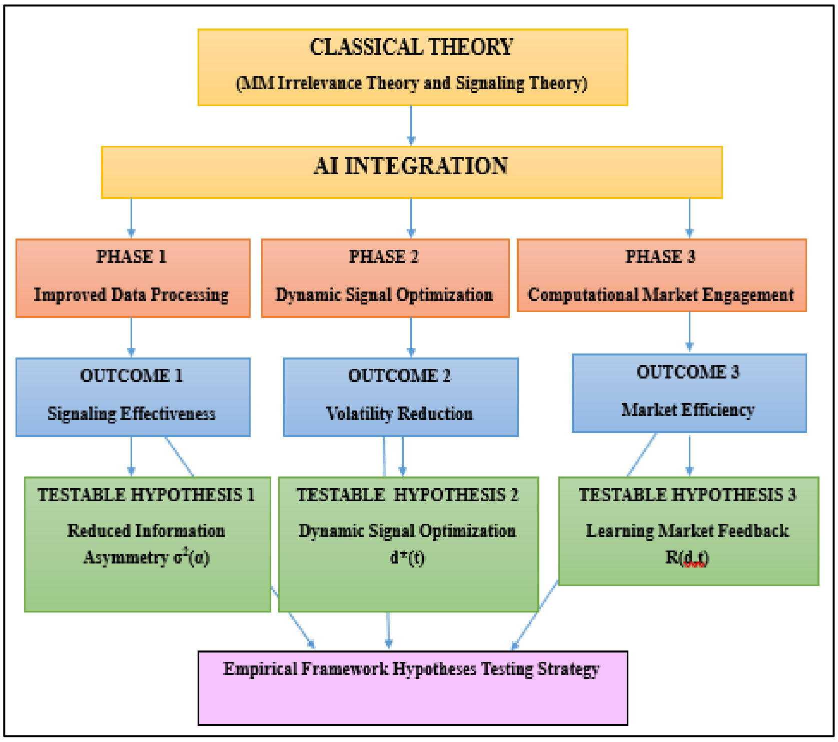

Figure 1 : Diagrammatic Representation of AI-Driven Dividend Signaling Model

Fig. 1 demonstrates the complete diagrammatic representation of the theoretical framework of AI-driven dividend signaling theory that explains how traditional signaling theory is transformed with AI adoption providing a better signaling effectiveness.

3. The AI-Driven Dividend Signaling Model

3.1 Model Specification

Assuming that the company operating the AI-enhanced dividend policy system has both algorithmic and human participants. Using the mathematical expression $\theta \in [\theta\_L, \theta\_H]$ indicating the quality of the firm, $\alpha \in [0,1]$ explains the AI competence level, and $I(\alpha)$ shows the capacity of processing the information, with $I'(\alpha)>0$. Consider the artificial intelligence algorithm that employs the data set $\Omega\_AI=\{\Omega\_human \cup \Omega\_extended\}$, where Ω_human indicates the accessible information to human participants and $\Omega\_extended$ includes all real-time market information, sentiment analysis, and analytical forecasts. Market participants include a fraction of algorithmic trading tools (β) and traditional human investors ($1-\beta$), who infer signals differently.

In the traditional signaling model,

$V = V(\theta, d)$ ---------- (1)

where 'V' indicates the value of the firm; 'θ' indicates the external factors affecting the firm and its intrinsic type (market conditions, investor sentiments about the firm, etc.); and 'd' symbolizes the dividend signal (Filatotchev et al., 2025).

With the application of artificial intelligence, the modified representation is

$V = V(\theta, d, \alpha, I(\alpha))$ ---------- (2)

where α indicates the level of AI competence, which can affect signaling effectiveness and data processing capability.

Considering equations (1) and (2), the problem of optimization of a firm's value can be expressed as

$\max_d V(\theta, d, \alpha, I(\alpha)) - C(d, \theta, \alpha)$ ---------- (3)

where 'V' is the value or revenue of the firm, and 'C' is the cost associated with the function of 'θ' expressing the external factors and firm's intrinsic type (high or low-performing); 'd' indicates the dividend signal, and 'α' and 'I(α)' represent the AI adoption level and the data collected from AI, respectively. The cost incurred out of AI adoption is unlike the traditional costs, as the asymmetry of the information is less compared to the traditional methods ($\partial C/\partial \alpha<0$), and evident optimization of dividend signaling is possible with the help of AI algorithms. According to the traditional theory, it is believed that the data disparity is static, but in the current market scenario, it is observed that there is swift evolution in the financial markets as there is fresh information being generated in an unpredictable manner, which plays a crucial role in market fluctuation. With the help of artificial intelligence, the information can be channelized, and the information disparity becomes endogenous. Consider if deviation in confidence of market participants in the firm ($\sigma^2(\alpha)$) at the AI adoption level (α) is represented by the mathematical expression

$\sigma^2(\alpha) = \sigma^2 o \cdot e^{\wedge}(-\lambda\alpha)$ ---------- (4)

where $\sigma^2 o$ indicates the baseline deviation without AI adoption (when $\alpha=0$) and $\lambda\alpha$ expresses the rate at which the information asymmetry is controlled by AI adoption. When $\lambda>0$, the AI adoption level decreases the data disparity, causing lower deviation considering the degree of signaling in AI adoption by the firm between 0 and $1(\alpha \in [0,1])$. Further, the degree of signaling between 0 and 1 is categorized into three different signaling phases:

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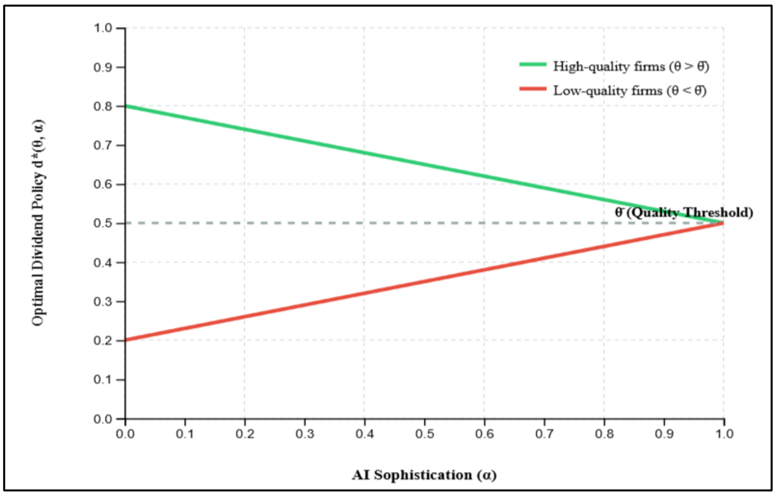

Figure 2: Relationship between AI Adoption (α) and Information Disparity ($\sigma^2(\alpha)$)

Fig. 2 illustrates that in the first phase, when $\alpha \in [0, \alpha_1]$, information disparity reduces without altering the signaling mechanism as the AI adoption level is limited to the enhancement of information processing. In the second phase, when $\alpha \in [\alpha_1, \alpha_2]$, the AI algorithm is improved to higher capabilities to actively reduce the information disparity by aligning with the real-time information, producing information-sensitive dividend signals, which can be expressed as d*(t)=argmax_{d} E[V (θ, d, α, t)│Ω_AI(t)] – C(θ, d, α, t), where d*(t) is the optimal dividend signal at time 't' and Ω_AI(t) is the level of dataset available to the AI adoption at 't'. In the third phase, when $\alpha \in [\alpha_2, 1]$, the AI adoption level reaches 1, which is the most advanced phase, where firms adopt an algorithmic-driven model completely in determining dividend policy. The model can alter the signals autonomously based on the corporate decisions, market sentiments, forecasts, and other fresh information. This helps in enhancing the accuracy of dividend signals to the market participants, forming an equilibrium condition traditionally and algorithmically.

4. Theoretical Considerations and Empirical Implications

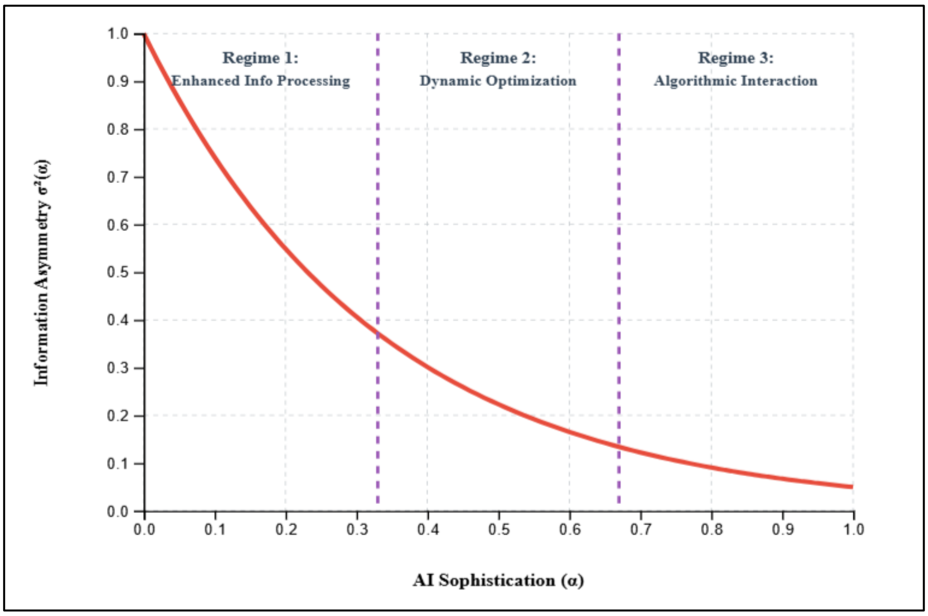

Figure 3: Optimal dividend signal d*(θ, α) at different intrinsic types of the firm

While developing the AI-Driven Dividend Signaling model, there are a few considerations being put forth to ensure more clarity and precision based on the existing literature.

Proposition 1: The intrinsic type of the firm, expressed by θ, has a significant impact on the optimal dividend signaling when AI algorithms are utilized. From the previous studies, it is evident that the quality of the signals produced by the high- and low-performing firms varies substantially. Consider that the optimal dividend signal is represented by $d^*(\theta, \alpha)$, where α is the level of AI adoption.

Fig. 3 illustrates that higher-performing firms can achieve signaling effectiveness easily with larger information availability and reduced signaling cost as the quality level is above the threshold ($\theta>\bar{\theta}$). In lower-performing firms, the signaling effectiveness can be achieved through progressive AI adoption and strategic investment in signaling as the quality is lower than the threshold ($\theta<\bar{\theta}$).

Proposition 2: When a firm integrates artificial intelligence in determining the dividend decision signal, it improves its capability to lower information disparity and enhances optimization of the dividend signals connected to its financial health, growth opportunities and performance.

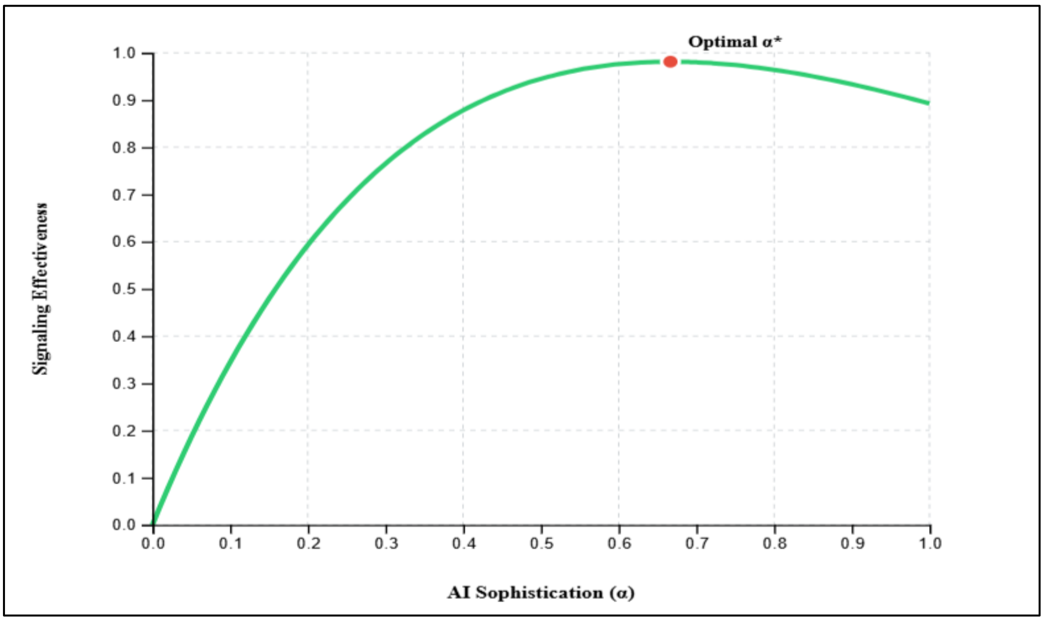

Figure 4: Relationship between Signaling Effectiveness and AI Adoption (α)

Fig. 4 illustrates the relationship between AI adoption level (α) and signaling effectiveness. In the initial stages of AI adoption (when $\alpha=0$), firms obtain an extensive advantage from the decline in uncertainty and transparency upsurge compared to the conventional method. When α reaches 1 and the data disparity becomes 0, the level of signal effectiveness is maximum (α^*), with reduced signaling cost prompting the corporate decisions to become completely algorithmic. Beyond the maximum, the marginal advantage of added AI adoption can decline as the market participants have almost complete information and the signals grow to be autonomous gradually. Thus, the relationship between signaling effectiveness and AI adoption level is not always unidirectional which can be expressed as $\partial^2(\text{Signaling Effectiveness Level})/\partial\alpha^2<0$.

Proposition 3: When the firms are totally algorithm-driven in dividend decision-making, the signaling effectiveness is optimal because it is based on real-time information, creating a dynamic and context-sensitive market environment. If the market participants also adopt AI technology effectively for decoding the signals, the signaling system becomes more efficacious as both the companies and market participants are incorporating AI in market analysis, resulting in dual equilibrium both traditionally and algorithmically.

To validate the theoretical framework, several hypotheses are formulated for testing after taking into account the different intrinsic types of firms, information disparity, AI adoption level, signaling effectiveness, and the discussed propositions. The analytically testable hypotheses are

H1: Firms with AI-driven dividend policies are associated with lower levels of information disparity and analytical dispersion and increased forecasts of expected returns.

H2: During volatile market conditions, AI-adopting firms disclose more strategic and optimal dividend announcement timing aligned with the real-time market behavior.

H3: The signaling effectiveness of AI adoption is stronger in markets with higher algorithmic trading volumes based on the firm-specific characteristics.

H4: A firm's signaling pattern varies with shifts in AI adoption level, indicating the phase-switching behavior consistent with phase transitions.

To empirically evaluate this theoretical framework, secondary information, such as data on AI adoption indicators like patents, technological investment disclosures, publicly disclosed textual reports of the firms (annual reports, public notices, etc.), financial data, real-time information like algorithmic trading volumes and dividend announcement timing, firm-specific characteristics, and related variables should be employed using sequenced AI-driven methods and econometric analysis tools to understand the causal associations and forecasting ability of the model (Chatterjee et al., 2021). Such information can help in identifying the variation of dividend signal frequently and cross-sectionally, providing stronger inference. Event studies, placebo tests, and evaluation of other alternate proxy variables for AI integration and signaling effectiveness, etc., can be used to do robustness checking of the study.

Conclusion

This paper presents a novel theoretical framework of AI-driven dividend signaling theory, hypothesizing how artificial intelligence transforms traditional dividend signaling approaches into an algorithmic mechanism in corporate finance by categorizing the relationship between information disparity and AI adoption into three different phases and also indicating non-unidirectional effects on the signaling effectiveness. This research study confronts the existing traditional signaling theories and discusses the importance of improvisation for better results using digital advancement in financial analysis. This model lays a groundwork for research in computational corporate finance by proposing that information disparity, dynamic optimization, and signaling phase transition can be affected by AI adoption collectively. This provides new insights for the corporate policymakers in strategic and optimal decision-making with AI adoption and also for the market participants on decoding the signaling pattern for AI-adopted firms. Future research should focus on understanding how AI adoption is affecting corporate finance, especially on building smarter financial models for decision-making by understanding the AI algorithms; cross-national and industrial level data analysis using AI adoption; and legal, scientific and behavioral integration in corporate finance as artificial intelligence is getting more advanced day by day towards deep neural networking, generic AI, etc., enhancing high accuracy and transparency in the market conditions. This research can help in increasing a firm's value and managing risks in financial decision-making.

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