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Building Trust in Transition:
The Nepal Ethical Capital Market AI (NECMA) Framework

Shashank Shree Neupane[1*]
Bibek Ropakhati[2]

**Corresponding Author*

Abstract

This study attempts to look into the ethical issues involved in AI integration in Nepal's capital markets, which are unique characteristics of the market structure, including a herd prone retail sector, behavioral herding, and underdeveloped technological infrastructure. By conducting theoretical and policy-based analyses that will integrate the AI policy of Nepal, NRB guidelines, OECD guidelines, and EU AI Act, we formulate the Nepal Ethical Capital Market AI (NECMA) framework based on the Technology-Organization-Environment (TOE) framework. The paper find that ethical governance is more than compliance; rather, it is a pre-requisite for the sustainable development of the financial sector in emerging economies. It is shown that the specific structural vulnerabilities of Nepal call for a sequential technology, environment, organization, and ethics filter.

Keywords: Algorithmic trading, emerging markets finance, ethical framework, regulatory sandbox, systematic risk

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INTRODUCTION AND STUDY OBJECTIVES

Capital market digitalization has followed a trend of rapidly increasing speed and drastically decreasing friction. Technology has rigorously tried to boost up the liquidity and price discovery through de-materialization of physical stocks and regulating electronic order books (Riordan & Storkenmaier, 2012) But a qualitative change is brought about by the Fourth Industrial Revolution. It involves the shift from rule-based, deterministic automation to autonomous, probabilistic artificial intelligence (AI). In contrast to their predecessors, AI agents are now driven by Reinforcement Learning (RL) and Deep Learning (DL). These possesses the capacity to learn from interactions from the surroundings, predict volatility with non-linear modeling, and execute decisions without explicit human interventions (Charpentier et al., 2023; Kelly & Xiu, 2023).

For western developed markets, this transformation is incremental evolution with

[1]Mr. Neupane and Mr. Ropakheti are faculty member at Presidential Graduate School, Westcliff University.
[2]They can be reached through shashankneupane@westcliff.edu and r.bibek@ncit.edu.np

a mature regulatory landscape. Institutions there are arguing the differences of "explainabil-ity" and "algorithmic collusion" against a backdrop of established high-frequency trading regulations and robust surveillance mechanisms (Breckenfelder, 2019; Brogaard et al., 2014). However, the introduction of AI offers developing nations' frontier and emerging economies a "leapfrog" potential with asymmetric dangers. These markets are in short of institutional investors who help to stabilize the prices often relying on volatile retail sentiment (Chaudhry et al., 2022).

An excellent example of this developing market dilemma is Nepal. The Nepal Stock Exchange (NEPSE) has witnessed an explosion in retail participation, driven by the MeroShare platform and Trade Management System (TMS) platform, which democratize access to primary and secondary markets for every citizens (Rawat, 2025). However, this digital accessibility subdues critical structural problems, like low economic literacy, a tendency to follow the crowd, and a regulatory framework, the Securities Board of Nepal (SEBON), is still pacing up to compete with basic market modernization (Devkota & Dhungana, 2019). As third-party applications begin to introduce AI-driven data analytics, signal generation, and portfolio tracking to this novice user base, the potential for "automation bias" and systemic and strong manipulation grows exponentially (Rijal, 2022).

This paper investigates a little-explored niche in academic literature. Even though many works have been published on the topic of the use of AI technologies in global finance and on financial inclusion in emerging economies, there is still little literature that attempts to combine these fields in one study. Two critical questions arise from this. Firstly, how can a small retail-oriented country such as Nepal benefit from the efficiencies of AI without being caught up in their potential for exploitation? Secondly, how does the international regulation on AI, e.g., OECD Principles on AI and EU AI Act, function in countries that cannot even monitor the markets electronically?

This research explores these queries by developing a conceptual framework grounded in the Technology-Organization-Environment (TOE) theory (Baker, 2012). The paper stated that ethical AI in Nepal depends on the simultaneous development of organizational capability in the domain of both brokerage knowledge and environment regulation controlled by institutions such as SEBON and NRB and not simply technological advances.

2. AI in Capital Markets: The Modes of Transformation

The ethical aspects of artificial intelligence in finance cannot be comprehended without understanding the underlying transformations and changes in mechanisms in capital allocation. At present, financial systems tend to utilize data, make predictions, and automate complex decision-making processes that were done by humans before.

2.1 Algorithmic Trading and Execution: From Rules to Reinforcement

Algorithmic trading (AT) has been traditionally applied as a conventional method to execute large orders through order fragmentation to reduce market impact. However, recent integration of AI has radically transformed these mechanisms of execution (Hasbrouck & Seppi, 2001).

Reinforcement Learning (RL) in Execution: Modern trading algorithms tend to use reinforcement learning that is a type of machine learning when an agent learns the best behavior via reward/penalty mechanism. In a trading setting, the "reward" is the financial return adjusted for risk, while "penalties" refer to losses or high transaction costs. Different from the rule-based systems, RL agents adapt to changing conditions all the time. Empirical research proves that RL systems significantly improve the quality of trade execution, volatility prediction, and assessment of systematic risks (Gašperov et al., 2021; Isaac et al., 2024).

High-Frequency Trading (HFT): In western markets, AI-driven HFT are responsible for a significant portion of cash flow. These systems operate on fractions of second and exploiting minute change in price across exchanges or anticipating order flows (Menkveld, 2016). These HFT systems concentrates market power and improves liquidity and it significantly reduces bid-ask spreads. The International Monetary Fund (IMF) notes that algorithmic trading enhances informational efficiency but can increase short-term volatility, particularly during stress events when algorithms may simultaneously withdraw liquidity (Bisias et al., 2012).

Predictive Analytics and Alpha Generation: AI is used for trading, even more, it is being used to generate excessive returns: 'alphas'. AI uses historical price data and financial knowledge, non-linear patterns are identified which is easily missed during human analysis (Zhang et al., 2019). For example, CNNs and LSTMs based deep learning models can correlate macroeconomic indicators with sector specific stock movements to predict price orientation with better accuracy compared to traditional linear regression models. (Briola et al., 2020; Morariu-Patrichi & Pakkanen, 2021)

Robo-Advisory and the Democratization of Wealth Management

An AI program called 'robo-advisor' addresses the financial needs of consumers. These applications use algorithms to evaluate a client's financial accomplishments and risk tolerance, automating the investment advisory process. These platforms ultimately automatically allocate assets into a diversified portfolio (Belanche et al., 2019).

Three levels of AI are used in these systems: a) Mechanical AI that automates repetitive operations, b) Thinking AI that uses data processing to make decisions and, b) Feeling AI, which reacts to user feelings. Researches suggests that AI driven personalization systems improves user satisfaction and has an ability to enhance portfolio performance by up to one third by using genetic algorithms and hybrid (Jung et al., 2018). For growing markets, these tools have critical significance for financial inclusion and lowering the cost hindrances significantly in professional wealth management (Manlapaz et al., 2024).

Sentiment Analysis: The Quantification of Psychology

Perhaps the most disruptive application in the AI subdomain is Natural Language Processing (NLP), whose marketplaces are dominated by a wealth of information that is especially unstructured. Basically news articles, social media posts, central bank statements, commercial banks' reports and earning call transcripts create this information overload (Tetlock, 2007).

NLP models (like BERT or GPT-based architectures) scrape millions of text data points to measure the sentiments of the market (Araci, 2019). In sentiment analysis terms like "bullish," "bearish," or "neutral" are used to classify text and a confidence score is assigned. Studies show that investment systems that analyses social media sentiment can achieve over % accuracy while predicting short-term market directional changes which is far better than traditional technical analysis (Alalmai, 2025). This capacity transforms qualitative noise into a quantitative signal, enabling traders to respond with millisecond sensitivity. On the contrary this capability also convert market into highly susceptible to 'narrative economics' and disinformation (Shiller, 2017).

Surveillance and RegTech

As AI adoption accelerates across financial markets, regulatory bodies are intensifying their oversight efforts. In Nepal, the Asset (Money) Laundering Prevention Act mandates that regulatory authorities flag entities involved in suspicious transactions-a process increasingly automated through AI systems (Abubakar et al., 2024). The Nepal Rastra Bank's AI Guidelines (2025) specifically identify compliance monitoring and risk management as critical application areas for AI technologies. These guidelines require Licensed Institutions to deploy sufficiently robust AI systems capable of detecting irregularities and mitigating operational failures. This regulatory direction effectively institutionalizes AI's role within Nepal's regulatory technology (RegTech) landscape (Bauguess, 2017).

Ethical Challenges in the Algorithmic Age

Incorporating AI into financial markets presents both an ethical conundrum and a substantial technological advancement. While delegating credible decisions to machines, concerns of accountability, fairness and market integrity are generated (Martin, 2019).

The "Black Box" Problem and Explainability

"Black Box" phenomenon is one of the most influential ethical challenge. Advanced AI models like Deep Neural Networks (DNN), works in layers of abstraction that hide the relationship between different inputs and outputs (Citron & Pasquale, 2014 ; Pasquale, 2015).

Financial decisions must make sense. The stakeholders, regulators, and victims must be informed if an AI-enabled credit scoring system rejects a loan or if a trading algorithm causes a stock or market fall. However, this black box effect doesn't allow anyone, even developers to trace the decision logic (Lundberg & Lee, 2017). Every party's fundamental right to know the explanation is in contradiction with this lack of transparency. This theme has been the core value of both the OECD Principles and the EU AI Act (European Commission, 2024). This opacity results in delayed diagnosis of the algorithm's failure point and the ultimate outcome hindered rapid remediation and prolonged systematic stress (Bodhale, 2025).

Algorithmic Bias and Discrimination

AI-based systems rely on past data that was used to train the models. Data with historical prejudices like racial bias in lending or gender bias in credit scoring might enforce AI to learn and replicate these biases ultimately amplifying them (Barocas & Selbst, 2016; Kordzadeh & Ghasemaghaei, 2022).

In western context, AI trained with historical loan data from the period of discrimination will learn that certain demographics have high risk, which will effectively automate discrimination under the guise of mathematical neutrality (Pethig & Kroenung, 2023). This also applies to developing markets like Nepal. Here, the available data is frequently fragmented or sparse. If a specific group who is vulnerable and lacks digital footprints is assessed using a "proxy variables" (e.g., phone usage patterns) for credit scoring, they will be discriminated (Cozarenco & Szafarz, 2018).

Market Manipulation and Information Asymmetry

While AI reduces barriers to market manipulation, it also generates new types of information asymmetry. Generative AI has the ability to generate realistic "deepfakes" or even fake news articles which can skyrocket the price of a stock (Mizuta, 2020). If a deepfake of the governor of NRB is generated where he announce increment in interest rate then it could trigger stock sell-off immediately (Yagemann et al., 2020).

The "arms race" for the best AI creates a tiered market. Larger players equip with supercomputers and proprietary datasets have a competitive edge against a retail investors (Bongaerts & Achter, 2021). This hinders the ethical principle of equality which leads to the exploitation of less sophisticated market players (Lomnicka, 2001).

Systemic Risk: The Danger of Homogeneity

Creating "model monoculture" is a subtle but critical ethical risk. If every assets managers utilize similar AI models trained with similar datasets and optimized with similar risk metrics, they will behave similarly and the resulting action becomes correlated (Danielsson et al., 2022). However, during times of market stress, many different algorithms - despite being diverse - may give the same buy/sell signal because of their reliance on the same training sets and the similar optimization goal of the traders. As a result, there may be coordinated trading behavior that leads to immediate disappearance of market liquidity and turns what was initially a small price movement into a systemic crisis. It is noteworthy that even the IMF warned about this possibility.

Lack of Human Accountability

One of the most important issues that arise in relation to liability is the issue of who should be held liable for decisions made by algorithms. For example, imagine a situation where an automated trader conducts himself through market manipulation in the form of spoofing without any conscious human participation. This creates the question of accountability, as there is no "intent" (mens rea) required for criminal liability under the existing laws (Abbott, 2020; Hallevy, 2010; Wendehorst, 2020).

Nepal's Capital Market Context: The Case Study

Nepal is a frontier market with unique structural characteristics that can increase certain risks associated with AI while reducing others. Hence we need to devise concrete frameworks from the abstract ethics considering the ground reality of Nepal. (Thomas et al., 2022).

Market Structure: The Retail Revolution and its Vulnerabilities

The Nepal Stock Exchange (NEPSE) has seen the radical transformation in the last decades. While developed markets are dominated by pension funds and HFT firms, NEPSE is highly retail driven (Adhikari et al., 2025). The industry has altered as a result of the adoption of TMS and the MeroShare platform. There are now more users. This huge influx of novice and retail investors forms 'digital herd.' These individuals lack formal financial literacy and depends excessively on digital tools for access, increasing the market sensitivity through UI design and algorithmic recommendations (Gajurel, 2019).

Behavioral Finance: The "Clubhouse Economy" and Herding

NEPSE shows prominent behavioral biases. Research show a significant pattern of "herding behavior," where individuals follow the trend of the market rather than financial indicators (Risal & Khatiwada, 2019). The exchange of trading advice in unregulated social media spaces and instant messaging apps is known as the 'clubhouse economy.' While professional investors are dubious in nature the retail investors uses such applications and portals as a primary source of information (Mohideen & Vigneshwar, 2024). There are several opportunities for AI-driven manipulation in such an environment. If AI bots were used to infiltrate these applications and social media to seed false narratives, the resulting herd movement could result in massive destabilization (Giri & Gurung, 2025).

The Current State of Technology Adoption

Due to skill gaps and legacy infrastructure, deep institutional AI is still in its infancy in Nepalese financial institutions like banks. Nonetheless, the "retail tech" industry is quickly integrating AI characteristics. Third-party applications offer "AI-driven analysis" and "algorithmic trading strategies." But issues of AI hallucination and dependency on global data but irrelevant data to Nepal's specific market dynamics, creates a tension between marketing hype and reality (Bhandari, 2025).

The Regulatory Gap

There exists a regulatory regime which has yet to come together within Nepal concerning the regulation of financial technology. The Securities Board Act 2062 (2006) makes no mention of regulations pertaining to algorithmic trading platforms or robo-advice systems. While the later Commodities Exchange Market Act 2074 encourages an electronic trading network that is safe from any vulnerabilities, there is nothing equivalent in terms of regulating the stock market. In contrast, the Nepal Rastra Bank's AI Guidelines (2025) make use of a risk-based categorization system whereby AI systems with an impact on financial stability are considered "high risk" (Nepal Rastra Bank, 2025).

Regulatory Benchmarks: Adaptation of International Standards

There are several international regulatory practices that could serve as benchmarks for Nepal. It is not necessary to invent an entirely new set of standards but rather adapt the already existing international standards, considering the specific market depth of Nepal.

OECD Principles on Artificial Intelligence

Organisation for Economic Co-operation and Development has laid down a "soft law" framework focusing on inclusion, centrality of humanity, transparency, accountability, and resilience. In case of Nepal, accountability principle gains special relevance. Regulators are blamed for any financial loss sustained by retail investors and, thus, the importance of clear liability systems differentiating between developers, adopters, and users of AI is emphasized (FSB, 2017; Tierno, 2025).

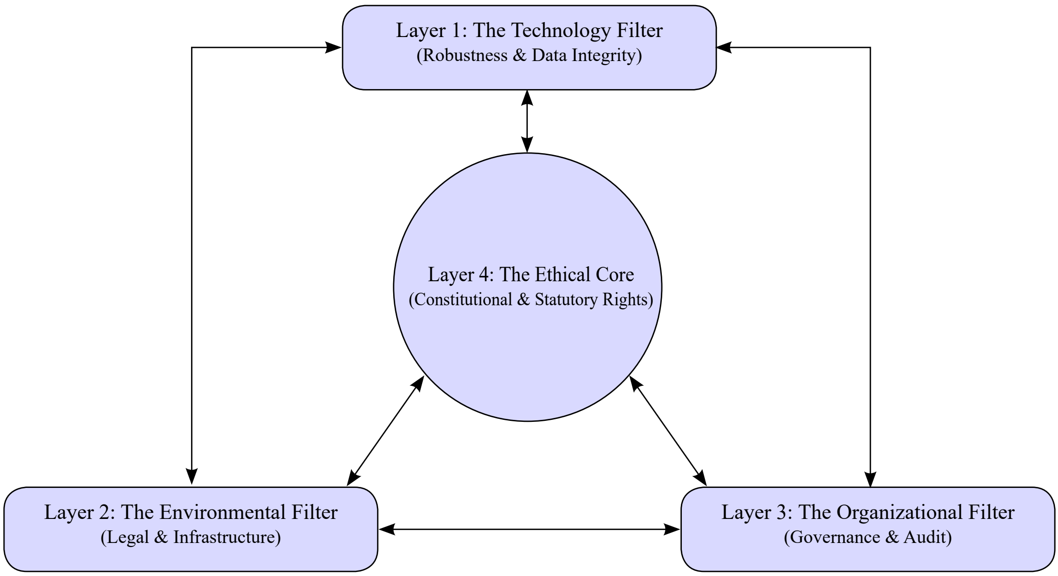

Figure 1. *The Nepal Ethical Capital Market AI (NECMA) Framework Structure*

The EU AI Act: A Risk-Based Approach

One of the world's first and most comprehensive AI laws is the AI Act of the European Union. This Act designates AI as "High-Risk" when it comes to credit rating and risk assessment. It is crucial for financial sector and is subjected to strict obligations in the aspects of quality of data, documentation and human oversight (Cecchetti et al., 2025 ; European Commission, 2024). In order to avoid automated and biased margin calls, Nepal must implement this classification for its market lending environment. Additionally, it might cause market spirals (European Union, 2024).

The World Bank & Developing Economies Perspective

The World Bank prioritizes using regulatory sandboxes and SupTech in developing economies (Pazarbasio et al., 2020). This idea is appropriate for Nepal, hence it must be investigated. Artificial intelligence (AI) can help regulatory agencies detect fraud that conventional approaches might overlook, which might be a force multiplier given Nepal's limited capacity for oversight.

Proposed Ethical AI Framework for Nepal

The paper propose the Nepal Ethical Capital Market AI (NECMA) Framework. This framework has been proposed by synthesizing the theoretical insights of the Technology-Organization-Environment (TOE) framework (Handayani & Mahendrawathi, 2019 ; Tornatzky & Fleischer, 1990) with the ethical principles of the OECD and the risk classifications of the EU.

Theoretical Basis: The TOE Framework

According to the TOE paradigm, three contexts-technological readiness, organizational competency, and environmental regulation-have an impact on technology uptake. We must take ethics into account in the context of Nepal. For ethical AI implementation, we are changing this framework to include a four-element model.

The NECMA Framework Structure
The figure below illustrates the NECMA Framework.

Concentric filtering is how the Nepal Ethical Capital Market AI (NECMA) Framework functions. Our hypothesis, which is based on the Technology-Organization-Environment (TOE) paradigm, is that an AI system must pass through four stringent filters in order to be accepted in Nepal's capital market: technological, environmental, organizational, and ethical. This arrangement makes sure that innovation doesn't beyond the market's structural ability to absorb it.

Layer 1: The Technological Filter (Robustness & Data Integrity) The first layer in this framework is the Technological Filter. Before any regulatory or ethical considerations, the AI model must prove its technical aspects specially within the specific context of Nepal's volatile market. Failure in passing this filter results in catastrophic failure.

Concept Drift Management: Financial markets are non-stationary systems subject to "concept drift". The statistical properties of the target variable change over time in such scenario. A model trained on the bull market of 2020 may fail catastrophically during a liquidity crunch. Our framework precisely focus that all the AI models being deployed must utilize adaptive learning mechanisms or periodic retraining schedules. These mechanisms and schedules must be validated by "ProteuS"-style stress testing in order to detect and adjust to regime shifts without manual intervention.

Data Quality and Sovereignty: In line with the "Garbage In, Garbage Out" (GIGO) principle, high-quality input data is a prerequisite for algorithmic fairness (Theodorakopoulos, 2025). This layer must enforce strict data cleaning protocols so that noise from Nepal's often fragmented financial data is removed. Furthermore, cybersecurity protocols that treat AI models must be incorporated. These models are critical infrastructure thus we need to defend it against model inversion and data poisoning attacks (Adeosun et al., 2025).

Layer 2: The Environmental Filter (Legal & Infrastructure) Once first filter approves the system, it must align with the external legal and physical environment of Nepal. It includes laws, bylaws, regulations and directives as well as infrastructure.

Statutory Compliance: The Electronic Transactions Act of 2063 must be carefully adhered to by any AI-driven financial models. Electronic records are only given legal validity if they are properly prepared and stored.

Infrastructure Localization: Dependency on third parties is a serious weakness for an inexperienced and expanding market like Nepal. Data localization needs to be given top priority in order to reduce such dangers. In keeping with the Cloud and Data Center Service Directives, 2081, all the financial data of Nepali Citizens must be must be hosted in local and tier rated data centers. Only those data should be used by AI models. This ensures data sovereignty and compliance with government security audits (Nepal Rastra Bank, 2025).

Operational Resilience: Operational resilience is very important for AI implemented systems. On the basis of the NRB AI Guidelines (2025), systems must show "Safe Failure" capabilities. If the AI encounters an unknown fault like network blackout, it must fail gracefully. All the trading needs to halt rather than executing erroneous orders, which thereby preserves systemic stability.

Layer 3: The Organizational Filter (Governance & Audit) The third layer emphasize the Organization factor. This layer addresses the firm's internal ability to manage the AI throughout its life cycle.

AI Steering Committees: Every firm must establish a "cross-disciplinary AI steering committee". It must comprise data scientists, compliance officers, and board members, as per NRB guidelines (Nepal Rastra Bank, 2025). This shift the organizational accountability from the IT department to the boardroom and will increase the management liability.

Mandatory Algorithmic Audits: Algorithmic audits helps to confirm security and compliance. In accordance with the Cyber Security Bylaw, 2077, capital market institutions using AI must conduct internal security audits every six months. Under NECMA, this audit is expanded to include "Model Risk Management" (MRM), validating algorithms not just for security, but for bias, accuracy, and interpretability (Leo et al., 2019).

Human-in-the-Loop (HITL): For "high-risk" AI systems like automated margin calls or credit scoring, human oversight must be mandatory. This oversight must be substantive, meaning the human operator has the competence to challenge and override the AI's recommendation, preventing "automation bias".

Layer 4: The Ethical Core (Constitutional & Statutory Rights) The final and most critical filter is the ethical layer. It ensures that AI respects the fundamental rights of Nepali citizens.

Privacy & Consent: Grounded in Article 28 of the Constitution of Nepal (Right to Privacy) and Privacy Act (2018), AI systems must obtain "explicit consent" from the users before processing their data for profiling. Users must be informed not just that data is being collected, but specifically that it will be used to train autonomous decision-making systems (Bodhale, 2025). All the possible usage and mechanisms of data storage must also be transparent.

Fairness & Anti-Discrimination: The framework emphasizes eliminating "algo-rithmic bias" against marginalized communities (Female, Dalits, Differently Able and indigenous nationalities), as protected by Articles 40 and 42 of the Constitution. AI models used for credit scoring must be tested for "disparate impact" to ensure they do not use proxy variables like geography and caste to institutionalize caste-based or ethnic discrimination (Kordzadeh & Ghasemaghaei, 2022; Utz, 2024).

Transparency (Right to Information): In line with Article 27 of the Constitution, customers have a right to know if they are interacting with an AI. The framework mandates clear labeling like "AI Generated Advice" and requires that decisions affecting financial access be explainable, utilizing different techniques to provide reasons for the decisions like loan denials or risk classifications (Bodhale, 2025).

POLICY IMPLICATIONS

Legislative Reform: The Securities Act Amendment

In order to implement the NECMA framework, reformation is required. The Securities Board Act should be amended to explicitly define “Artificial Intelligence Systems” and “Algorithmic Trading.” SEBON should adopt the NRB’s definition of high-risk AI to harmonize regulations and expand market manipulation provisions to include AI-driven acts like quote stuffing (Lomnicka, 2001). Overall, all the governing agencies need to establish a consortium and reform the existing Securities Board Act, followed by issuing the required regulations as well.

Supervisory Capacity: The “SupTech” Mandate

Multiple agencies have been formed and are in operation for proposing different laws and policies related to AI and its usage. SEBON should collaborate with the proposed AI Regulation Council and other stakeholders to establish a specific capital market sandbox (Alaassar et al., 2022; Chen, 2020). This would allow fintech companies to test AI tools under a regime that waives certain reporting requirements temporarily, provided consumer protection is maintained (Ahern, 2021). This SupTech approach empowers the close monitoring of AI use in different agencies.

Infrastructure and Cyber Resilience

Capital market institutions must align with Cyber Security Bylaws. This includes maintaining a Security Operation Center (SOC) and Disaster Recovery Plan to ensure an AI flash crash does not wipe out investor data (Abubakar et al., 2024).

CONCLUSION

The introduction of AI technology to the capital market in Nepal is inevitable. Given the global momentum in the area of technologies, coupled with demand from local people for convenient digital financial services, AI trading and advising tools will quickly become ubiquitous in the future. Nonetheless, this study identifies an important aspect of using AI technologies in the financial market - if the pursuit of efficiency is not accompanied by an implementation of proper ethical frameworks, instability might be generated.

The proposed NECMA framework offers a way out to this problem. It includes three components: the need for algorithmic transparency, human involvement in the decision-making process, and regulation sandboxes that will allow for conducting experiments on a controlled environment. Such steps are required in order to leverage the benefits offered by the use of AI in the market without compromising the market’s integrity. The aim should not be a prevention of innovation; it must ensure that the market remains controlled by humans and not some opaque algorithms. For developing countries, incorporating ethics into the process of AI application is essential.

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