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**Original Research Article**

# Advanced Decision Analytics in Brokerage Operations and Capital-Market Efficiency in Saudi Arabia under Vision 2030

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**Abstract:** Saudi Arabia's capital market is moving from scale expansion toward deeper institutionalization, digital participation, and sophisticated trading infrastructure. Brokerage firms sit at a critical interface between investor intentions and exchange-level outcomes. This review examines how advanced decision analytics can improve brokerage operations while supporting liquidity, price discovery, resilience, and investor confidence under Vision 2030. A structured integrative review synthesized 30 peer-reviewed and institutional sources published from 2020 to 2025 across market microstructure, algorithmic and high-frequency trading, machine learning, reinforcement learning, financial risk analytics, securities regulation, and Saudi market development. Five analytics domains emerge: client and order intelligence, execution optimization, liquidity and market-making analytics, real-time risk and compliance, and operational resilience. Evidence indicates that analytics can reduce implementation shortfall, improve order routing and inventory control, and accelerate information incorporation into prices; however, benefits depend on market design, liquidity regimes, model governance, and automated participant behavior. Saudi evidence is timely because algorithmic and high-frequency traders now represent material shares of liquidity while market-making and post-trade infrastructure are expanding. The paper proposes a Saudi Brokerage Decision Analytics Framework linking governed data, predictive and prescriptive models, human oversight, execution controls, and market-quality metrics. Decision analytics should therefore be treated as a governed market capability whose success is measured jointly by brokerage efficiency and market integrity.

**Keywords:** Decision Analytics, Brokerage Operations, Market Microstructure, Algorithmic Trading, High-Frequency Trading, Saudi Exchange, Vision 2030, AI Governance.



## 1. INTRODUCTION

Saudi Vision 2030 has accelerated a broad restructuring of the Kingdom's financial system, with capital-market development positioned as a mechanism for economic diversification, private-sector financing, investment attraction, and more efficient allocation of savings. The Financial Sector Development Program explicitly seeks a deeper and more liquid market with stronger participation by local and foreign investors, while the Capital Market Authority's 2024-2026 strategy places financing, investment, institutional development, and international competitiveness at the center of market policy (Financial Sector Development Program, 2024; Capital Market Authority, 2024).

Brokerage institutions are central to this transition because they transform investor demand into executable orders, manage connectivity to trading venues, control pre-trade and post-trade risks, and increasingly provide algorithmic execution, analytics, and digital investment services. Modern decision analytics expands this function by combining statistical learning, machine learning, optimization, explainable artificial intelligence, and real-time market data to support or automate decisions across the brokerage value chain (Milana & Ashta, 2021; Goodell *et al*., 2021; Aziz *et al.*, 2022). The operational question is therefore not simply whether brokers should use artificial intelligence, but which decisions should be analytically augmented, what evidence supports those applications, and how benefits can be transmitted to market quality.

Saudi Tadawul Group reported that high-frequency traders contributed about one quarter of average daily trading value in 2024 and substantially more on peak days, while algorithmic traders contributed up to 40% of daily liquidity. The same period saw wider market-making coverage, tighter spreads, deeper books for securities with active market makers, and new controls such as automated order cancellation on disconnection and enhanced trade monitoring (Saudi Tadawul Group, 2024). Annual market statistics also show a sharp increase in trading activity during 2024, with value traded and the number of executed trades growing strongly relative to 2023 (Saudi Exchange, 2025).

Yet greater automation does not automatically produce greater efficiency. Research on high-frequency and algorithmic trading reports benefits such as tighter spreads, faster information incorporation, and more continuous liquidity, but it also identifies adverse possibilities, including anticipatory trading, commonality in liquidity, model-driven crowding, and stress-period withdrawal (Baldauf & Mollner, 2020; Hirschey, 2021; Ramos & Perlin, 2020). Flexible models can improve prediction and risk classification, but their complexity can weaken explainability, increase dependence on data quality, and create model risk when outputs are embedded directly in trading decisions (Mashrur *et al.,* 2020; Černevičienė & Kabašinskas, 2022).

This review addresses a gap between three bodies of literature that are often examined separately: financial machine learning, electronic-market microstructure, and Saudi capital-market development. The emphasis is on operations that are directly relevant to brokers - order intake, execution, market making, risk, surveillance, client service, and resilience - and on market-efficiency outcomes that can be observed through spreads, depth, price discovery, implementation shortfall, continuity, and confidence.

**2. Aim, Review Questions and Objectives**

The aim of this review is to synthesize evidence published from 2020 to 2025 on advanced decision analytics in securities markets and translate that evidence into a Saudi-specific framework for improving brokerage operations and capital-market efficiency. Four review questions guide the synthesis: which analytical capabilities create the highest operational value for brokers; through which microstructure mechanisms can those capabilities affect liquidity and price discovery; which Saudi market developments enable or constrain adoption; and which governance controls are required to prevent analytical sophistication from undermining fairness, resilience, or investor protection.

Five objectives follow from these questions. First, the review maps data, predictive models, optimization methods, and reinforcement learning to concrete brokerage decisions. Second, it evaluates evidence connecting automated trading and analytical execution with spreads, market impact, information efficiency, and liquidity. Third, it interprets recent Saudi market infrastructure and policy developments through the lens of brokerage analytics. Fourth, it identifies model, conduct, cyber, concentration, and operational risks associated with data-driven brokerage. Fifth, it proposes an implementable framework in which analytical performance, human accountability, and market-quality metrics are evaluated together rather than as separate technology and compliance agendas.

## 3. REVIEW METHODOLOGY

A structured integrative review design was used because the question spans heterogeneous evidence: empirical market-microstructure studies, machine-learning reviews, quantitative trading research, regulatory guidance, and Saudi institutional reports. A conventional meta-analysis would be inappropriate because the studies examine different markets, outcomes, sampling frequencies, models, and regulatory settings. The integrative design therefore supports comparison of mechanisms, operating implications, risks, and governance conditions rather than pooled effect sizes.

The review window was restricted to 2020-2025, matching the period in which machine learning, algorithmic execution, and modern Saudi market infrastructure became especially relevant. The search strategy combined terms for decision analytics, artificial intelligence, machine learning, reinforcement learning, brokerage, trade execution, market making, high-frequency trading, liquidity, price discovery, Saudi Exchange, Tadawul, and Vision

2030. Scholarly material was located through academic search and publisher-indexed records, while institutional material was retrieved from official Saudi and international regulatory repositories. Eligible academic sources had to address electronic-market efficiency, financial AI, execution or market-making optimization, or Saudi stock-market efficiency and governance.

Screening proceeded in three stages: title and abstract or executive-summary relevance, full-text relevance to a brokerage decision or market-quality mechanism, and final verification of publication year and bibliographic identity. Duplicate, pre-2020, weakly related, or unverifiable items were excluded. The final analytical corpus contains 30 sources listed in the references. Academic studies were treated as empirical or methodological evidence; institutional documents were used for policy, infrastructure, governance, and current Saudi market context. Key institutional sources include the CMA, Financial Sector Development Program, Saudi Exchange, Saudi Tadawul Group, IOSCO, Financial Stability Board, NIST, and U.S. Securities and Exchange Commission (IOSCO, 2021; Financial Stability Board, 2024; NIST, 2023; U.S. Securities and Exchange Commission, 2025).

Each source was coded against one brokerage domain: client and order intelligence, execution, market making, risk and compliance, or operational resilience. Evidence was then mapped to spread, depth, volatility, price discovery, information leakage, market impact, and continuity. Enabling conditions and risks were compared across sources, with particular attention to contradictory findings because emerging-market evidence cautions against assuming uniform liquidity effects from automation (Ramos & Perlin, 2020). The result is an integrative conceptual framework, not a claim that a particular algorithm will generate a fixed improvement in Saudi market quality. Because the review is integrative rather than exhaustive, the search and synthesis are reported transparently but are not presented as a PRISMA systematic review.

## 4. Conceptual Foundation: Decision Analytics and Market Microstructure

Decision analytics is broader than predictive modeling. In brokerage operations it combines descriptive information about the current state of the order book, predictive estimates of prices or liquidity, and prescriptive logic that recommends an action under constraints. Machine learning is useful when relationships are nonlinear, high-dimensional, or continuously changing; optimization is needed when the broker must select among competing objectives such as speed, price, risk, and market impact. Reviews of financial AI show that forecasting, risk assessment, portfolio decisions, fraud detection, and market analysis have become major application clusters, while explainable decision methods remain important where decisions must be challenged or audited (Ozbayoglu *et al.,* 2020; Warin & Stojkov, 2021; Černevičienė & Kabašinskas, 2022).

Market microstructure provides the transmission mechanism from brokerage decisions to capital-market efficiency. Aït-Sahalia and Brunetti (2020) find that periods with greater high-frequency participation can coincide with improved liquidity conditions, while Ben Ammar and Hellara (2021) identify a bidirectional relationship between high-frequency activity and price efficiency. Bhattacharya *et al*., (2020) show that HFT participation can facilitate the assimilation of earnings information, and Saliba (2020) finds that aggressive HFT orders may contain short-horizon information.

Hirschey (2021) documents an anticipatory channel through which some high-frequency traders infer and trade ahead of slower order flow, potentially raising costs for other investors. Baldauf and Mollner (2020) model a liquidity-information trade-off in which faster trading can improve spreads yet weaken incentives for information production. Ramos and Perlin (2020), using emerging-market evidence, find that algorithmic activity can worsen liquidity measures, demonstrating that market maturity and institutional design matter. Yang *et al*., (2020) similarly show that optimal quoting and liquidity depend on volatility, latency, and the arrival of other traders and news.

For brokerage decision analytics, the implication is clear: operational optimization must be constrained by a market-quality objective. A model that minimizes a client's execution cost by exploiting predictable order flow may be profitable yet harmful if it increases information leakage or adverse selection elsewhere. Conversely, a market-making model that maximizes spread capture without inventory and stress controls may withdraw precisely when liquidity is most valuable. Advanced analytics therefore requires multi-objective governance in which commercial performance, client outcomes, operational stability, and market integrity are treated as simultaneous decision criteria.

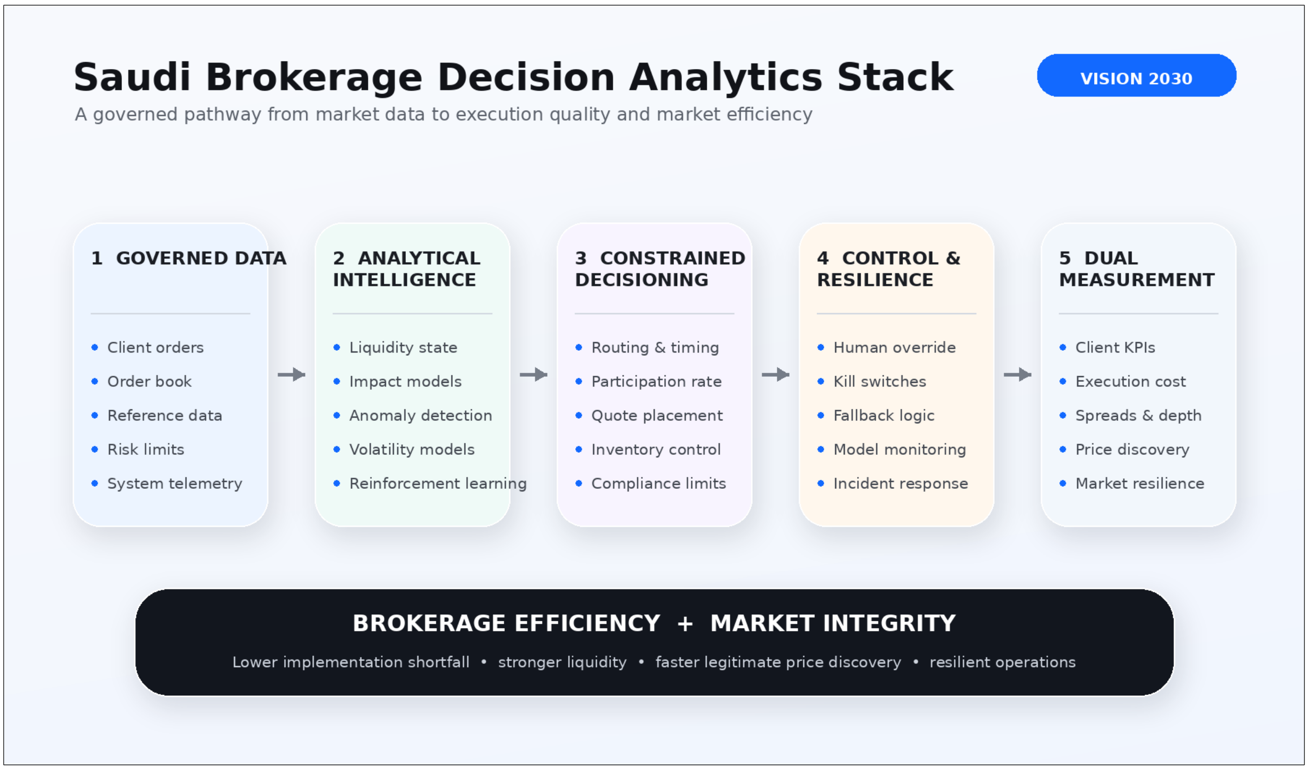


**Figure 1: Saudi Brokerage Decision Analytics Stack. Source: author synthesis based on the reviewed 2020-2025 literature**

## 5. Saudi Capital-Market Readiness under Vision 2030

Saudi Arabia's market-development agenda creates strong demand for this multi-objective approach. The Financial Sector Development Program identifies deeper capitalization, improved liquidity, and stronger domestic and foreign participation as conditions for an advanced capital market (Financial Sector Development Program, 2024). The CMA strategy for 2024-2026 similarly emphasizes expanding the market's financing and investment role, strengthening institutions, and improving international competitiveness (Capital Market Authority, 2024). Brokerage analytics can support these objectives because transaction quality affects the willingness of investors to allocate capital, particularly when institutional investors evaluate execution quality, transparency, and operational reliability alongside expected return.

Market infrastructure has advanced in ways that make analytical brokerage more feasible. Saudi Tadawul Group describes increased algorithmic and high-frequency participation, broader equity market making, enhancements to derivatives, improved FIX connectivity, automated cancellation following member disconnection, drop-copy monitoring, and synchronized market-maker quoting (Saudi Tadawul Group, 2024). These are not merely technical upgrades. They create data streams, control points, and execution mechanisms that brokers can incorporate into real-time decision systems. They also increase the importance of deterministic controls because faster connectivity compresses the time available for manual intervention.

The scale of activity reinforces the relevance of operational analytics. Saudi Exchange reported that 2024 share-trading value reached SAR 1.862 trillion, while the number of trades rose to 128.57 million and traded volume reached 99.66 billion shares (Saudi Exchange, 2025). At the same time, Saudi Tadawul Group reported that high-frequency traders represented approximately 25% of average daily trading value and algorithmic traders contributed up to 40% of daily liquidity (Saudi Tadawul Group, 2024). Once automated participation reaches this magnitude, broker-level algorithms can materially influence order-book dynamics, and poorly coordinated models can amplify rather than absorb shocks.

Saudi market efficiency has also evolved institutionally. Al-Faryan and Dockery (2021) find evidence that corporate-governance change was associated with improvement in weak-form efficiency across subperiods of the Saudi stock market. Their result supports a broader point: efficiency is shaped by governance and institutional design, not only by technology. Decision analytics should therefore be seen as the next layer of market capability, built on governance, disclosure, infrastructure, and investor participation. Vision 2030 creates the strategic rationale, while recent exchange developments create the operational foundation. The remaining challenge is to ensure that analytics is deployed in a way that scales liquidity and sophistication without scaling opaque risk.

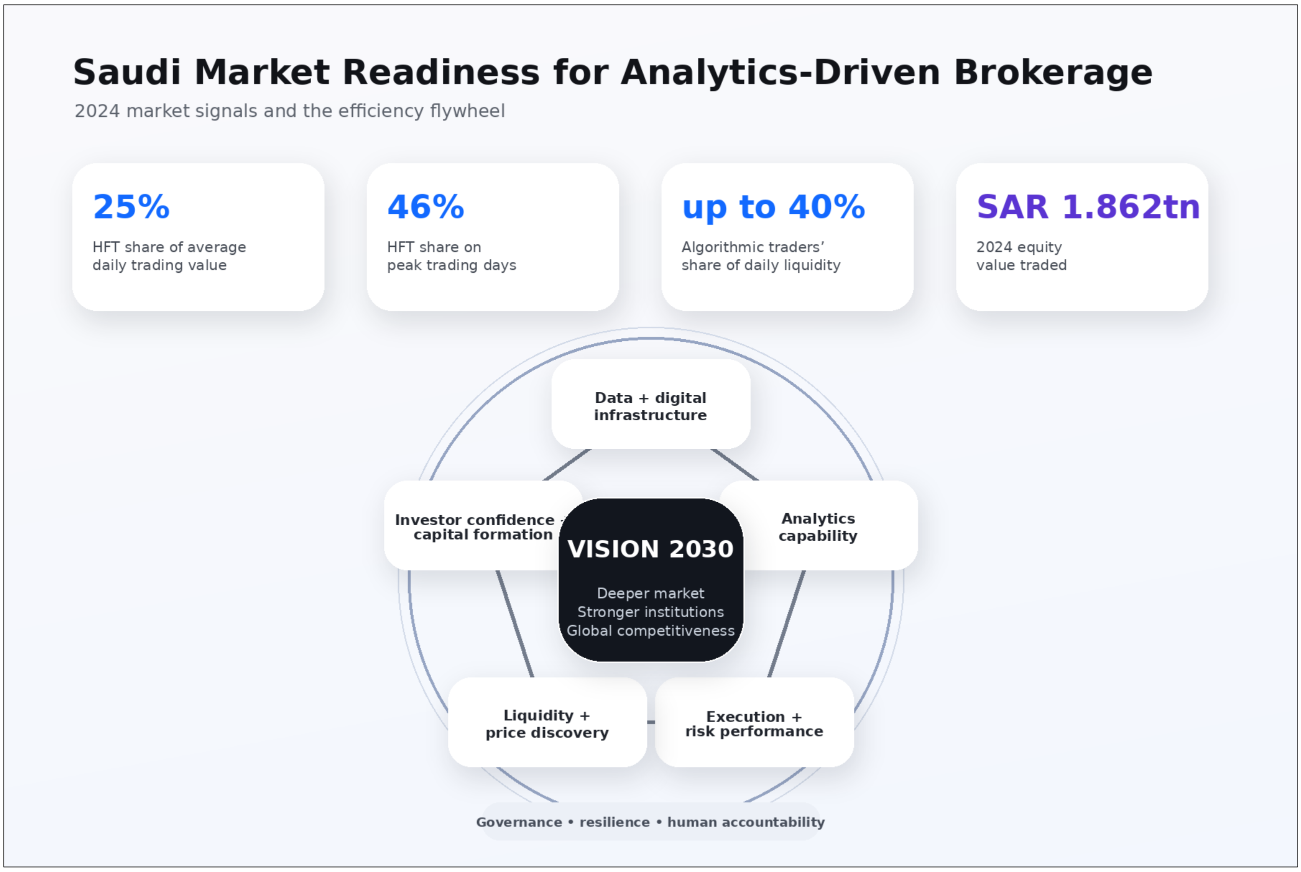


**Figure 2: Saudi electronic-market readiness and the brokerage analytics flywheel. Sources: Saudi Tadawul Group (2024) and Saudi Exchange (2025); 2024 market data**

## 6. Decision Analytics across Brokerage Operations

The first high-value domain is client and order intelligence. Brokerage firms receive heterogeneous orders that differ by urgency, size, benchmark, risk tolerance, and information sensitivity. Machine-learning asset-pricing evidence demonstrates the ability of nonlinear methods to extract useful signals from large predictor sets, particularly momentum, liquidity, and volatility variables (Gu *et al*., 2020). In a brokerage setting, the objective is not to predict long-term returns for proprietary speculation, but to use conditional forecasts to choose an execution schedule that reflects the order's constraints.

The second domain is execution optimization. Transparent benchmarks such as VWAP and TWAP remain useful, but they do not fully adapt to changing intraday states. Deep reinforcement learning treats execution as sequential decision making in which each action changes remaining inventory and future opportunity. Byun *et al*., (2023) demonstrate a practical DRL approach that adapts execution across stocks, time horizons, and target volumes and outperforms a VWAP benchmark in their setting. The result does not justify direct transfer to Saudi equities, but it shows how granular order-book data and realistic simulation can support adaptive execution. For Saudi brokers, a prudent design would combine an adaptive policy with hard constraints on participation rate, price collars, maximum child-order size, and kill-switch conditions. Performance should be assessed through implementation shortfall, benchmark slippage, fill rate, rejection rate, and adverse price movement after trades.

The third domain is market making and liquidity provision. Market makers continuously choose bid and ask quotes while managing inventory risk, queue position, volatility, and expected order arrivals. Reinforcement-learning research shows that models can incorporate predictive signals into quoting and improve reward-to-risk performance relative to benchmark strategies (Gašperov & Kostanjčar, 2021). Market-microstructure studies likewise suggest that faster or more informed quoting can narrow spreads and accelerate price adjustment, although outcomes depend on who supplies liquidity and under what conditions (Aït-Sahalia & Brunetti, 2020; Yang *et al*., 2020). In Saudi Arabia, expanding designated market making gives analytical quoting a direct public-market function. Objectives should therefore include minimum presence, spread discipline, inventory limits, and stress-period continuity, not simply P&L.

The fourth domain is real-time risk and compliance. Machine learning is increasingly used for anomaly detection, risk classification, and pattern recognition across high-volume data, but financial-risk surveys emphasize data quality, concept drift, imbalanced outcomes, and interpretability as persistent challenges (Mashrur *et al*., 2020). A broker can use streaming analytics to detect unusual order bursts, self-trading patterns, deviations from client mandates, excessive concentration, or abnormal cancellation behavior. These models should prioritize escalation rather than autonomous enforcement when signals are ambiguous. Explainable multi-criteria approaches are particularly relevant because compliance decisions often require a traceable reason connecting data, threshold, rule, and action (Černevičienė & Kabašinskas, 2022).

The fifth domain is operational resilience. Advanced execution depends on market data feeds, order-management systems, exchange gateways, network connectivity, cloud or third-party services, and model-serving infrastructure. IOSCO's work on operational resilience shows that sudden surges in order and trade volumes can strain venues and intermediaries, while its market-outage report emphasizes business continuity, communication, alternative arrangements, and orderly reopening (IOSCO, 2022; IOSCO, 2024). Saudi Tadawul Group's automated cancel-on-disconnect and monitoring enhancements are examples of infrastructure controls that can be embedded in brokerage decision architecture (Saudi Tadawul Group, 2024).

Across these domains, the strongest operating model is a hierarchy rather than a single artificial-intelligence engine. At the base, data quality and event-time synchronization establish a reliable state of the market and client order. The next layer estimates liquidity, volatility, fill probability, market impact, and operational risk. A decision layer selects an execution or control action subject to regulatory, client, and risk constraints. Finally, a monitoring layer compares realized outcomes with expectations and feeds errors back into model validation. This architecture aligns with the broader literature showing that machine learning adds most value when it improves prediction while organizational controls translate predictions into disciplined decisions (Milana & Ashta, 2021; Easley *et al*., 2021).

**Table 1: Brokerage decision-analytics domains and market-efficiency pathways**

| Brokerage domain | Analytics focus | Primary decision | Operational KPIs | Efficiency pathway |
|---|---|---|---|---|
| Client & order intelligence | Order size, urgency, benchmark, liquidity-state models | Execution style, schedule and aggressiveness | Implementation shortfall; fill rate; benchmark slippage | Lower execution cost and smaller market footprint |
| Execution optimization | Order-book forecasting, impact estimation, optimization / RL | Routing, timing, participation and child-order placement | Market impact; completion rate; realized spread | More disciplined liquidity consumption and price discovery |
| Market making | Inventory, volatility, flow and quote-response analytics | Bid-ask quotes, sizes and inventory rebalancing | Quote presence; spread capture; inventory risk | Tighter spreads, depth and continuous liquidity |
| Risk & compliance | Rules, anomaly detection, behavioral patterns and explainability | Block, review, escalate or permit activity | Alerts; false positives; limit breaches; review time | Market integrity, fairness and controllable automation |
| Operational resilience | Latency, gateway, feed and infrastructure telemetry | Failover, cancel-on-disconnect, fallback mode | Uptime; latency; rejected orders; recovery time | Continuity, resilience and investor confidence |

## 7. From Brokerage Performance to Capital-Market Efficiency

The key contribution of advanced brokerage analytics is not automation itself but the possibility of improving market quality through repeated micro-level decisions. The first pathway is transaction-cost reduction. Better forecasts of spread, depth, and short-horizon volatility can reduce unnecessary aggressiveness and improve scheduling, thereby lowering implementation shortfall. When similar capabilities are distributed across brokers, trading interest can be matched more smoothly over time.

However, transaction-cost optimization should be evaluated net of signaling effects because aggressive or predictable slicing can reveal the presence of a large parent order.

The second pathway is liquidity. Evidence on automated trading is mixed. Baldauf and Mollner (2020) show how faster trading can improve spreads under certain mechanisms, while Aït-Sahalia and Brunetti (2020) find that lower high-frequency participation is associated with more problematic volatility and jump conditions. Saudi Tadawul Group reports tighter spreads and greater market depth for securities supported by market makers, alongside substantial algorithmic participation (Saudi Tadawul Group, 2024). Yet Ramos and Perlin (2020) demonstrate that algorithmic trading can worsen realized spreads and price impact in an emerging market. The policy lesson is to monitor liquidity quality, not simply automated-trading volume. Useful indicators include quoted and effective spreads, depth at multiple levels, cancellation intensity, recovery after large trades, and liquidity during volatile periods.

The third pathway is price discovery. Ben Ammar and Hellara (2021) associate greater high-frequency activity with more efficient intraday prices, while Bhattacharya *et al*., (2020) show that HFT participation can assist the incorporation of earnings information. Saliba (2020) similarly documents information in aggressive HFT orders. For Saudi brokers, advanced analytics can accelerate the conversion of public information into executable valuations, but regulators and firms must distinguish legitimate information processing from strategies that infer and exploit another investor's latent order. Hirschey (2021) shows why this distinction matters: anticipatory trading can shift costs toward slower participants even when prices become more informative.

The fourth pathway is market resilience and confidence. Efficient markets must remain operable under stress. A broker that optimizes normal-time execution but fails during data outages, capacity spikes, or model instability imposes costs on clients and potentially on the market. IOSCO (2022, 2024) therefore treats operational resilience and outage management as core elements of orderly markets. Under Vision 2030, where international participation and institutional depth are strategic goals, resilient analytics can become part of the market's credibility. The most meaningful efficiency metric is thus composite: lower transaction costs and faster information incorporation, achieved without sacrificing fairness, continuity, or controllability.

**Table 2: Evidence synthesis and implications for Saudi brokerage**

| Evidence theme | Representative 2020-2025 evidence | Observed direction | Saudi brokerage implication | Remaining gap |
|---|---|---|---|---|
| HFT and spreads | Baldauf & Mollner (2020); Aït-Sahalia & Brunetti (2020) | Liquidity benefits can coexist with information-production trade-offs | Use spread/depth gains alongside adverse-selection metrics | Saudi causal evidence by security and regime |
| HFT and price efficiency | Ben Ammar & Hellara (2021); Bhattacharya *et al.*, (2020); Saliba (2020) | Faster incorporation of information in several settings | Measure price impact and information leakage around automated flow | Local identification of informed versus anticipatory activity |
| Algorithmic trading in emerging markets | Ramos & Perlin (2020) | Possible wider spreads and greater liquidity commonality | Stress-test models for correlated liquidity withdrawal | Transferability to Tadawul market structure |
| Execution optimization | Byun *et al*., (2023); Easley *et al*., (2021) | Adaptive policies can improve sequential execution when simulation is realistic | Deploy shadow testing and market-impact constraints before automation | Live Saudi benchmark evidence and client-level outcomes |
| Market making | Gašperov & Kostanjčar (2021); Yang *et al*., (2020) | Analytics can improve quoting and inventory control | Balance quote presence, inventory risk and adverse selection | Performance across thin and stressed Saudi names |
| Responsible AI & resilience | IOSCO (2021, 2022, 2024); FSB (2024); NIST (2023) | Governance, model risk and operational controls are integral to safe scaling | Embed model ownership, kill switches, failover and vendor-risk controls | Common Saudi assurance metrics for brokerage AI |

## 8. Governance, Responsible AI and Regulatory Control

Governance is the condition that converts advanced analytics from a source of model risk into a controlled brokerage capability. IOSCO (2021) identifies governance and oversight, model development and testing, data quality, transparency, outsourcing, and ethical concerns as major control areas for AI and machine learning used by market intermediaries and asset managers. NIST (2023) similarly frames trustworthy AI through risk management across the system lifecycle. These principles imply that brokerage models should have named owners, defined intended uses, documented training data, validation thresholds, fallback procedures, and explicit authority for suspension.

Model risk is especially important because trading models learn from historical regimes that may not persist. A liquidity predictor calibrated during normal conditions may underestimate spread widening during stress, while an execution policy trained in simulation may exploit assumptions that do not survive real order-book feedback. Byun *et al*., (2023) highlight the importance of realistic high-granularity simulation, and the broader machine-learning literature repeatedly emphasizes out-of-sample validation and overfitting control (Gu *et al*., 2020; Ozbayoglu *et al*., 2020). Saudi brokers should therefore use walk-forward validation, regime testing, perturbation tests, and shadow deployment before expanding automated authority.

The U.S. Securities and Exchange Commission's 2023 predictive-data-analytics proposal illustrates regulatory concern that optimization technologies used by broker-dealers and investment advisers may interact with conflicts of interest. The SEC withdrew that proposal on 12 June 2025, so it is treated here as evidence of regulatory debate rather than an operative U.S. requirement (U.S. Securities and Exchange Commission, 2025). The issue remains transferable to brokerage governance: a model optimized for engagement, internalization, or proprietary economics may not maximize client execution quality. Firms should therefore define objective functions that can be audited against best-execution duties, client instructions, suitability, and internal conflict policies.

Systemic and concentration risks also grow as firms adopt similar models and common technology providers. The Financial Stability Board (2024) identifies third-party dependencies, market correlations, cyber risk, and model and data weaknesses as channels through which AI may amplify financial vulnerabilities. For Saudi brokerage, this supports controls over vendor concentration, correlated strategy behavior, shared-data dependencies, and cyber resilience. The governance objective should not be to slow useful innovation; it should be to ensure that faster decision cycles are paired with faster detection, escalation, and human intervention.

## 9. Proposed Saudi Brokerage Decision Analytics Framework

The evidence supports a five-layer Saudi Brokerage Decision Analytics Framework. Layer one is governed data. Brokers should integrate client-order attributes, exchange market data, reference data, risk limits, and operational telemetry into a synchronized event architecture with lineage and quality controls. Data used for model decisions should be time-stamped, versioned, and monitored for staleness. This layer creates the factual basis for both execution and post-event audit.

Layer two is analytical intelligence. Different problems require different methods: supervised learning for fill probability or market-impact estimation, unsupervised methods for anomaly detection, time-series models for volatility and liquidity states, and reinforcement learning for sequential execution or market-making decisions. The literature does not support a single superior method across all finance problems; reviews instead show a diversified methodological landscape whose effectiveness depends on data, objective, and validation design (Warin & Stojkov, 2021; Aziz *et al*., 2022). Model selection should therefore begin with the decision problem and required explainability rather than with the newest algorithm.

Layer three is constrained decision-making. Predictions should enter an optimization policy bounded by client instructions, CMA rules, exchange controls, risk appetite, participation limits, price collars, inventory limits, and operational thresholds. This layer is where commercial objectives are reconciled with market integrity. For market making, the objective may balance spread capture, inventory variance, quote presence, and maximum drawdown. For agency execution, it may balance benchmark cost, completion probability, information leakage, and adverse selection.

Layer four is human and automated control. Routine low-risk actions can be automated, but exceptions require clear escalation to traders, risk officers, compliance teams, and technology operations. Kill switches, cancel-on-disconnect, fallback algorithms, and manual routing are not signs of analytical weakness; they are resilience mechanisms. IOSCO's AI guidance and outage work support a control model in which authority, monitoring, and contingency procedures are designed before deployment rather than added after an incident (IOSCO, 2021; IOSCO, 2024).

Layer five is dual performance measurement. Brokerage success should be assessed through client and operational KPIs - implementation shortfall, benchmark slippage, fill rate, latency, rejection rate, inventory risk, and incident frequency - together with market-quality indicators such as spreads, depth, price impact, price efficiency, cancellation behavior, and resilience. This dual scorecard makes the Vision 2030 connection explicit. A broker contributes to a more advanced capital market when its analytics improves client execution while reinforcing liquidity, transparency, and confidence. The framework therefore treats market quality as an observable external outcome of internal decision architecture rather than as a separate regulatory concern.

### 10. Managerial and Policy Implications

For brokerage executives, implementation should proceed by decision criticality rather than by technology fashion. The most attractive first use cases are those with abundant data, measurable outcomes, and reversible actions: transaction-cost analysis, liquidity-state classification, order anomaly detection, and execution recommendations with trader approval. Higher-autonomy applications such as adaptive market making or fully automated execution should follow only after the firm has mature model validation, real-time controls, incident response, and independent challenge. This sequencing reduces the risk of creating sophisticated models on top of weak data or fragmented operations.

For the CMA and Saudi Exchange, the priority is to make analytical innovation measurable. Market-wide monitoring can examine how algorithmic intensity relates to spreads, depth, volatility, cancellation ratios, and stress-period liquidity across securities. Broker reporting could focus on governance and control outcomes rather than requiring disclosure of proprietary models. Regulatory sandboxes or controlled pilots may be useful for new execution or market-making approaches when success criteria include both firm performance and market quality. The evidence from Saudi Tadawul Group (2024) suggests that market-making incentives and infrastructure enhancements can improve trading conditions, but continued evaluation is needed as algorithmic participation grows.

For talent development, Saudi brokerage requires hybrid professionals who understand market microstructure, data engineering, quantitative modeling, compliance, and model governance. The decision analyst in a brokerage context must be able to question a model's economic logic, not only its statistical accuracy. This capability supports Vision 2030's broader objective of institutional sophistication because advanced markets depend on people who can connect technology, finance, and accountability.

### 11. Limitations and Future Research

This review has limitations. The 30-source corpus prioritizes integrative relevance over exhaustive bibliometric coverage, and much of the causal evidence on algorithmic and high-frequency trading comes from markets structurally different from Saudi Arabia. Reinforcement-learning studies also rely heavily on simulations or non-Saudi order books. Reported performance gains should therefore not be treated as transferable effect sizes, while institutional reports provide current context rather than independent causal evidence.

Future research should use Saudi order-level data to test whether algorithmic intensity improves effective spreads, depth, price discovery, and resilience across liquidity regimes. Studies should compare broker execution algorithms on implementation shortfall while controlling for order size, urgency, and information content. Market-making research should examine whether designated liquidity remains stable during volatility spikes. A further priority is model-governance research that measures how explainability, human override, and validation standards affect operational incidents. These questions would convert the conceptual framework proposed here into Saudi evidence base capable of guiding brokerage investment and regulatory design.

## 12. CONCLUSION

Advanced decision analytics can become a meaningful infrastructure layer for Saudi Arabia's capital-market transformation, but its value depends on the quality of the decisions it improves and the safeguards surrounding those decisions. Evidence from 2020-2025 supports applications in execution, market making, risk detection, and operational monitoring, while also showing that automation can produce adverse liquidity, conduct, and stability effects when incentives or controls are poorly designed. Saudi Arabia enters this phase with strong enabling conditions: rising algorithmic participation, expanding market making, modernized trading controls, higher trading activity, and a Vision 2030 policy agenda focused on deeper and more competitive financial markets.

The proposed framework therefore links governed data, fit-for-purpose analytics, constrained decision policies, human oversight, and dual performance measurement. Its central principle is that brokerage efficiency and market efficiency should be optimized together. When analytical models reduce client costs, strengthen liquidity, accelerate legitimate price discovery, and remain resilient under stress, brokerage innovation becomes a direct contributor to Vision 2030. When those conditions are absent, greater speed merely amplifies existing weaknesses. The strategic task for Saudi brokers and regulators is consequently to scale intelligence with accountability.

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