© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723547

Advanced Decision-Making Models for Digital Transformation of Brokerage Operations in Saudi Arabia

SAYYED RIZWAN HAJIMIYA
0009-0007-8893-747X

***Abstract-** Digital transformation within securities brokerage increasingly presents a decision-making challenge rather than a straightforward technology-acquisition issue. Brokerage firms must evaluate options such as artificial intelligence, robo-advisory, application programming interfaces, cloud infrastructure, process automation, advanced analytics, and hybrid advisory models, while concurrently safeguarding investors, managing model risk, ensuring regulatory compliance, and preserving trust. This review develops an integrative framework for advanced decision-making models customized to brokerage operations in Saudi Arabia. It integrates recent peer-reviewed evidence on financial artificial intelligence, robo-advisory, digital banking, explainability, algorithm aversion, customer adoption, and financial-service governance. The analysis contends that no single optimization model can drive Saudi brokerage transformation. Instead, it supports the combination of multi-criteria decision analysis, predictive analytics, scenario analysis, explainable artificial intelligence, and staged human governance. The proposed architecture connects strategic value, operational workability, customer outcomes, Shariah-sensitive design, data governance, cybersecurity, and regulatory accountability. The synthesis points to a continuing tension: although automation boosts scalability and consistency, insufficiently governed or opaque automation can diminish adoption and heighten operational, conduct, or reputational risks. Accordingly, the paper proposes an adaptive decision cycle in which digital initiatives are systematically diagnosed, prioritized, piloted, governed, and either scaled or discontinued based on measurable evidence. The review also identifies research gaps related to Saudi brokerage-specific datasets, comparative decision-model performance, Arabic explainability, investor heterogeneity, hybrid human–algorithm designs, and longitudinal regulatory outcomes.*

***Keywords:** Digital transformation; brokerage operations; Saudi Arabia; multi-criteria decision analysis; robo-advisory; artificial intelligence; explainable AI; fintech governance*

I. INTRODUCTION

Saudi Arabia's financial sector is shifting from digitized service channels to data-intensive, platform-based finance, where technology shapes advice, execution, compliance, risk management, and client relationships. Research on Saudi digital finance already documents strong institutional interest in artificial intelligence, digital banking, open banking, and robo-advisory, while also emphasizing trust, perceived usefulness, policy intervention, security, and user experience as conditions of adoption (Al-Baity, 2023; Alnemer, 2022; Ansari & Bansal, 2024; Mutambik, 2023). For brokerage firms, this transition is more demanding than simply transferring transactions to mobile interfaces. A brokerage operates a tightly coupled system of investor onboarding, suitability assessment, market access, order routing, portfolio analytics, research, advisory, surveillance, reconciliation, cyber controls, and regulatory reporting. Digital transformation therefore reallocates decision rights across people, algorithms, platforms, and external providers.

The literature demonstrates that artificial intelligence can improve prediction, personalization, service speed, and operational functioning within financial institutions; however, the magnitude of these benefits depends on the specific task and implementation context (Ahmed et al., 2022; Fares et al., 2022; Herrmann & Masawi, 2022; Singh et al., 2025). In investment services, robo-advisors exemplify this complexity. They facilitate scalable profiling and portfolio management, mitigate certain behavioral frictions, and enable lower-cost service delivery. Nevertheless, adoption continues limited because of factors such as algorithm aversion, privacy matters, absence of transparency in recommendations, and ambiguity regarding accountability (Aw et al., 2024; Filiz et al., 2022; Zhu, Pysander, & Söderberg, 2023). These data indicate that selecting technology solely on the basis of anticipated cost reductions or technical accuracy is insufficient.

A decision model for Saudi brokerage transformation must evaluate several objectives simultaneously. Financial value matters, but so do execution resilience, suitability, explainability, cybersecurity, customer inclusion, regulatory traceability, interoperability, vendor dependence, organizational capability, and conformity with Islamic-finance expectations. The decision is also dynamic: a solution attractive in a pilot may become inappropriate as market variability, regulation, customer behavior, data quality, or model effectiveness changes. Consequently, advanced decision-making should be treated as a portfolio-governance capability that repeatedly compares alternatives in conditions of uncertainty rather than as a one-time capital-budgeting exercise.

This review addresses that need through integrating research on digital finance with decision-oriented evidence from robo-advisory and AI-enabled financial services. The attached paper serves solely as a structural and academic-writing reference, rather than as a source of substantive findings. The main contribution of this review is to synthesize fragmented findings into a brokerage-specific architecture customized to Saudi Arabia. Multi-criteria prioritization determines which initiatives warrant resource assignment; predictive and scenario analytics estimate possible results; explainability and human monitoring enforce constraints on automated decisions; and feedback metrics inform the updating of priorities following deployment.

II. AIM OF THE STUDY

The objective of this study is to develop a critically synthesized, evidence-based framework for selecting, governing, and adapting digital-transformation initiatives within Saudi brokerage operations. Rather than seeking a single optimal technology, the review investigates how advanced decision models can integrate strategic value, operational performance, customer behavior, risk, explainability, and regulatory requirements when brokerage firms evaluate competing transformation routes.

III. RESEARCH OBJECTIVES

The review has five objectives: (1) to identify decision criteria that recur across recent research on AI-enabled financial services, robo-advisory, digital banking, and investment platforms; (2) to compare the strengths and limitations of multiple-criteria, analytical, behavioural, and governance-oriented decision approaches; (3) to interpret how Saudi-specific adoption evidence changes the weighting of trust, regulation, customer experience, and policy support; (4) to propose an integrated decision architecture for prioritizing and governing brokerage transformation initiatives; and (5) to identify research gaps that must be resolved before advanced models can be validated for Saudi brokerage settings.

IV. RESEARCH QUESTIONS

Four questions guide the review. First, which strategic, operational, technological, customer, and governance criteria should shape digital-transformation decisions in brokerage firms? Second, which decision-model families are most suitable for balancing those criteria in uncertain conditions? Third, how should Saudi institutional and behavioral conditions modify model design and implementation? Fourth, what evidence is still required to test whether integrated decision models improve brokerage outcomes rather than merely accelerate technology adoption?

V. REVIEW METHODOLOGY

A structured integrative review was selected because the topic spans information systems, finance, service management, behavioral economics, and regulation. The method merges systematic search discipline with critical synthesis across heterogeneous empirical and conceptual designs. Reporting principles follow PRISMA 2020, particularly transparent specification of eligibility, search logic, screening rationale, and synthesis limitations (Page et al., 2021). This paper reports no fabricated record counts because it does not claim a completed database-level meta-analysis with auditable screening logs.

The planned search domain covers Scopus, Web of Science Core Collection, ScienceDirect, Emerald Insight, Wiley Online Library, SpringerLink, and publisher platforms used to verify bibliographic records. Search strings combine brokerage-related terms with transformation and decision terms, for example: (“brokerage” OR “investment advisory” OR “robo-advisor” OR “wealth management”) AND (“digital transformation” OR “artificial intelligence” OR “automation” OR “fintech”) AND (“decision model” OR “multi-criteria” OR “adoption” OR “trust” OR “explainability” OR “risk” OR “governance”). Saudi-focused searches additionally combine “Saudi Arabia” with digital banking, open banking, robo-advisory, and AI in finance.

Inclusion criteria prioritize peer-reviewed journal articles published mainly between 2020 and 2025, written in English, and directly relevant to financial-service digitalization, automated investment advice, AI-enabled operations, customer adoption, algorithmic decision quality, explainability, or digital-finance governance. Saudi-specific evidence is retained even when it addresses adjacent financial services because empirical research on brokerage alone remains limited. Exclusion criteria remove non-peer-reviewed reports, theses, news items, purely technical trading papers lacking organizational relevance, and papers whose financial context is incidental. Older foundational literature may be appropriate in a larger review, but the present synthesis intentionally emphasizes recent evidence.

Quality assessment is design-sensitive rather than based on one universal checklist. Empirical studies are judged regarding clarity of sampling, construct validity, analytical transparency, robustness, and fit between evidence and inference. Review studies are judged on database scope, reproducibility, synthesis logic, and acknowledged limitations. Conceptual or regulatory analyses are assessed for internal logic and relevance to decision accountability. Evidence is then coded into six domains: strategic value, operational capability, customer/advisor interaction, analytical performance, risk and governance, and Saudi contextual fit. The synthesis uses thematic comparison and contradiction analysis instead than vote counting. Methodological limitations comprise database coverage, publication bias, fast technological change, inconsistent definitions of robo-advisory, and transferability risks when applying banking or international evidence to Saudi brokerage operations.

To improve reproducibility, future executions of this review protocol should export full bibliographic records, deduplicate by DOI and title, and retain a decision log for borderline records. Ideally, two reviewers would code a shared subset of studies before full extraction, reconcile disagreements, and refine the coding guide. Because the evidence base mixes experiments, surveys, qualitative studies, reviews, and conceptual analyses, synthesis should preserve design differences rather than collapse them into a single effect estimate. Evidence matrices can record context, sample, technology, decision task, dependent outcomes, governance features, and limitations. This approach grants structured comparison without implying statistical equivalence. Use citation chasing only to identify additional peer-reviewed studies that meet the same criteria. DOI and bibliographic details should be verified against Crossref or publisher records before inclusion. In a later full systematic review, exact identification, deduplication, exclusion, and inclusion counts should be reported from the saved search logs; they are deliberately not reconstructed here from memory or inferred from the reference list.

VI. THEMATIC LITERATURE REVIEW AND CRITICAL ANALYSIS

Recent reviews agree that financial AI has moved from isolated analytical applications toward broader service and process architectures. Ahmed et al. (2022) map applications across prediction, portfolio management, behavioral finance, and big-data analytics; Fares et al. (2022) organize banking AI around strategy, process, and customer domains; and Hentzen et al. (2022) show that customer-facing financial AI research remains split among technical performance and adoption behavior. Singh et al. (2025) extend the operational perspective by identifying explainability, inclusion, regulation, and customer readiness as continuing constraints. Together, these studies imply that brokerage transformation decisions should not rank projects solely by expected automation intensity. A high-performing model without process integration, customer legitimacy, or governance can destroy rather than create value.

The first decision domain is strategic and operational value. Digital platforms are able to lower marginal service costs, extend access, and standardize recurring decisions. Bhatia et al. (2021) found that investors associate robo-advisory with automated portfolio allocation and scalable wealth management, while Grealish and Kolm (2021) describe robo-advice as an app-based delivery model that broadens access to investment support. Helms et al. (2022), however, show considerable differences in design and performance among international robo-managers, weakening any assumption that automation itself assures better outcomes. Barile, Secundo, and Bussoli (2025) similarly conclude that fully automated and combined models reflect different business logics and that relying exclusively on algorithms can be inadequate for customers who require interaction. For Saudi brokers, operational value therefore depends on task decomposition: straight-through processing, surveillance, research support, onboarding, and portfolio rebalancing may justify different degrees of automation.

The second domain concerns investor profiling and decision quality. So (2021) shows the importance of systematic risk profiling, while Gaspar and Oliveira (2024) demonstrate that common profiling questionnaires can be vague and opaque about allocation logic. Cohen (2022) reviews advanced AI methodologies for trading and forecasting, illustrating the technical possibilities of data-based financial decisions, but prediction accuracy does not resolve suitability or governance questions. Back, Morana, and Spann (2023) provide an important behavioral counterpoint: robo-advice is able to mitigate the disposition effect, yet social design elements may reduce advice seeking. Eichler and Schwab (2024) likewise argue that robo-advisors cannot be assumed to eliminate behavioral bias because algorithm construction, expectations, and human interpretation remain part of the decision system. Thus, brokerage decision models should evaluate both algorithmic effectiveness and interface-induced behavior.

A third domain is adoption, trust, and perceived value. Hong et al. (2023) show that uncertainty-reduction mechanisms influence perceived value and investment intention. Belanche et al. (2025) find that customers weigh advantages against risks, including fear of financial loss and wasted time, while ease of learning and security shape that evaluation. Filiz et al. (2022) demonstrate persistent algorithm aversion even when the automated option is demonstrably efficient. These results warn against treating adoption as a communication problem that can be solved after technical deployment. Adoption variables are decision criteria at the investment-selection stage because they affect utilization, retention, cost-to-serve, and realized return on technology.

Explainability is especially consequential in investment services. Digmayer (2024) identifies barriers across configuration, matching, maintenance, and withdrawal when robo-advisors fail to answer users' information needs. Zhu, Pysander, and Söderberg (2023) find that users view automated advice as non-transparent and incomprehensible, and that data visualization offers one route to boost comprehension. Yang and Lee (2024) extend the discussion to generative AI financial advice and emphasize consumer perceptions of service value and acceptance of AI devices. These data support explainability as a design variable rather than a post-hoc compliance artifact. In brokerage operations, explanation should be calibrated to the decision: a client-facing suitability recommendation requires intelligible reasons, whereas a surveillance alert may require traceable feature contributions and an auditable escalation record.

A fourth domain is privacy, fairness, and accountability. Aw et al. (2024) show that perceived justice can reduce privacy worries and intrusiveness, suggesting that fairness perceptions influence resistance independently of functional performance. Marano and Li (2023) demonstrate that existing regulatory systems can leave inconsistencies around AI-enabled advice, particularly where responsibilities are implicit or disproportionate. Zhu, Vigren, and Söderberg (2024) synthesize the robo-advisory literature and call for implementation research that accounts for interactions among service robots, customers, organizations, and wider institutions. This evidence indicates that governance should be embedded within the transformation decision model. Projects with attractive revenue or efficiency cases may still be dominated alternatives if they cannot produce audit trails, support human override, manage model drift, or preserve customer data rights.

Saudi evidence changes the relative importance of those dimensions. Alnemer (2022) shows that usefulness, ease of use, trust, age, and education matter in Saudi digital-banking adoption. Mutambik (2023) links open-banking customer experience to ease of use, value, support quality, reliability, risk, and innovation. Al-Baity (2023) identifies strong potential for AI in Saudi digital finance while stressing moral and regulatory conditions. Most directly, Ansari and Bansal (2024) find that perceived usefulness, benefits, and policy measures positively influence Saudi robo-advisory adoption. These studies do not prove that the same coefficients apply to brokerage customers. Still, they establish a defensible contextual proposition: Saudi brokerage decision models should weight policy coherence, trust architecture, customer capability, and service quality more heavily than generic technology scoring models typically do.

The evidence also supports a portfolio rather than project view of transformation. Herrmann and Masawi (2022) describe the long evolution of AI across banking, financial services, and insurance, showing that applications mature at different rates. Arenas-Parra, Rico-Pérez, and Quiroga-Garcia (2024) find that robo-advisory research focuses on human-facing phases of the advice process, suggesting that unresolved interaction problems can become bottlenecks. Kumar (2025) shows that robo-advisors alter the wider advisory market rather than simply replacing one delivery channel. A brokerage should therefore evaluate complementarities among initiatives: data architecture may be a prerequisite to AI; digital identity may increase the value of automated onboarding; explainability tools may be necessary to scale decision automation; and human advisory capacity may become more valuable when routine activities are automated.

These data motivate an integrated model. Multi-criteria decision analysis can structure competing objectives, using methods such as AHP or ANP to elicit weights and TOPSIS

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723547

or VIKOR to rank alternatives. Predictive analytics estimates demand, operational impact, fraud or conduct risk, and model performance. Scenario analysis tests sensitivity to market, regulatory, and technology conditions. Explainability and governance add veto criteria for unacceptable risks. Figure 1 represents this architecture as an interaction among strategic inputs, operational data, technology options, constraints, analytical layers, governance, and a feedback mechanism. The critical principle is that ranking and control are connected: an initiative is not "optimal" merely because it scores highly before deployment; it must remain acceptable as evidence accumulates.

Decision quality also depends on data architecture. Financial AI applications require consistent identifiers, historical depth, accessible metadata, and reliable links between customer, account, instrument, transaction, and interaction data. Weak data lineage can make a sophisticated model less governable than a simpler rule-based workflow because errors become difficult to locate and explain. Accordingly, data readiness should be an independent criterion in the transformation score, not buried within implementation cost. Projects that share foundational data assets create complementarities: a client-data platform can support onboarding, personalization, surveillance, and service analytics, while a fragmented stack can force each project to recreate controls and interfaces. This is one reason portfolio sequencing matters as much as individual project ranking.

Vendor and ecosystem choices create a related decision problem. Brokerage firms increasingly rely on cloud providers, market-data vendors, model platforms, identity services, and fintech partners. Outsourcing may accelerate implementation and provide specialist capabilities, but it can concentrate operational dependency and complicate responsibility when models or interfaces fail. A mature decision model should therefore score portability, contractual audit rights, data residency, service continuity, model access, update governance, and exit feasibility. These criteria transform vendor selection from a price comparison into a resilience decision. They also support real-options logic: modular contracts and interoperable APIs preserve the option to switch technologies as evidence changes.

Workforce capability is another recurring but underdeveloped theme. Automation changes the content of brokerage work by shifting employees from repetitive processing toward exception handling, model supervision, client explanation, and control design. If staff cannot interpret model outputs or challenge vendor claims, nominal human monitoring can become ceremonial. Training should therefore be evaluated as part of the technology investment rather than as a downstream change-management expense. The strongest operating model is not necessarily the one with the smallest human role; it is the one in which human attention is concentrated on uncertain, material, or relationship-sensitive decisions while routine work is consistently automated.

Table 1. Evidence domains for digital-transformation decisions in brokerage operations

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723547

Decision domain	Evidence from literature	Implication for Saudi brokerage
Strategic and operational value	AI and robo-advisory can improve scale, standardization, service speed, and cost efficiency, but platform performance varies.	Score value by workflow; distinguish onboarding, research, surveillance, execution, advisory, and back-office use cases.
Investor decision quality	Risk profiling and analytical models can support consistency, yet questionnaires and model logic may be opaque.	Require validation of suitability logic, profiling quality, and behavioural effects, not technical accuracy alone.
Adoption and trust	Perceived value, security, uncertainty reduction, and algorithm aversion influence use.	Treat adoption as an ex-ante economic criterion; test trust and comprehension during pilots.
Explainability	Incomprehensible advice reduces confidence and adoption; explanation needs differ by task.	Specify client explanations, internal model evidence, and audit trails by decision type.
Privacy, fairness, accountability	Privacy and justice perceptions affect resistance; legal responsibility for AI can be ambiguous.	Apply hard governance gates for data rights, human override, escalation, and third-party accountability.
Saudi contextual fit	Saudi evidence emphasizes usefulness, policy intervention, trust, service quality, and digital-finance ethics.	Adjust criterion weights to local evidence and validate with brokerage-specific data rather than assuming generic global weights.

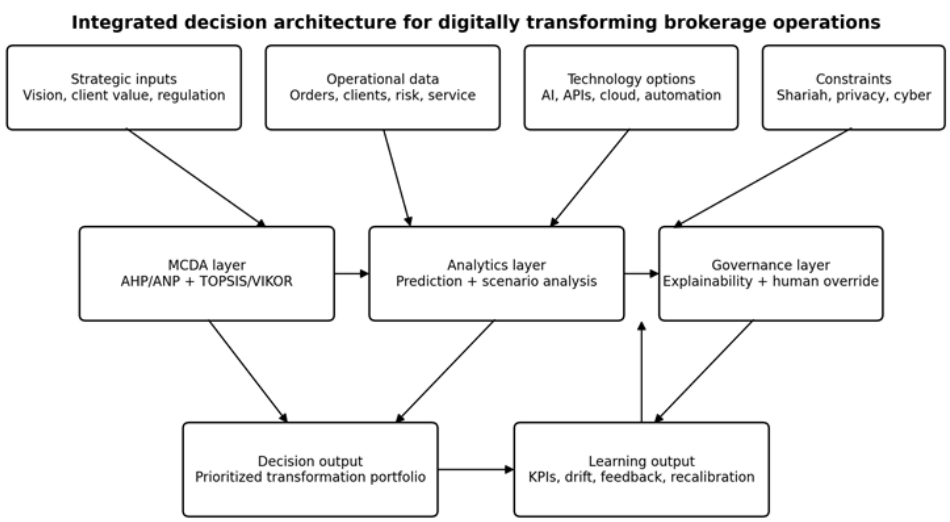

Figure 1. Integrated decision architecture for digital transformation of brokerage operations.

The figure shows that strategic and operational inputs are ranked through MCDA, informed by analytics, constrained by governance, and updated through feedback.

VII. DISCUSSION

The synthesis indicates that advanced decision-making for brokerage transformation should combine compensatory and non-compensatory reasoning. Compensatory models permit strong performance on one criterion to offset weakness on another; this is useful for comparing cost, speed, scalability, and revenue effects. Yet some brokerage risks should be non-compensatory. A material suitability failure, unmanageable cyber exposure, an inability to explain an automated recommendation, or the absence of accountable human escalation should operate as a constraint or veto rather than a low score that can be

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723547

offset by projected profit. The architecture therefore needs two layers: a ranking layer for strategic prioritization and a governance layer that defines minimum acceptability.

This distinction clarifies why pure technology scorecards are inadequate. A brokerage choosing between automated advisory, AI-assisted research, intelligent order surveillance, cloud migration, and API-enabled client integration faces alternatives with incomparable benefit structures. MCDA creates a common decision language, but weights should not be treated as objectively true. They express priorities that may differ among management, risk, compliance, investment professionals, and clients. Robustness requires sensitivity analysis, stakeholder-specific weights, and explicit documentation of disagreements. Where rankings change materially with small weight adjustments, management should treat the choice as uncertain and favor pilots or reversible investments.

The literature also supports hybrid intelligence. Barile et al. (2025) and Zhu et al. (2024) show why human–AI configurations deserve separate evaluation from fully automated designs. Human involvement can improve exception handling, empathy, accountability, and explanation, while algorithms can improve consistency, scale, and monitoring. The relevant decision is therefore not “human versus machine” but which tasks should be automated, augmented, reviewed, or prohibited from autonomous execution. Saudi brokers can embed this distinction in operating models by assigning decision rights based on client impact, model uncertainty, transaction materiality, and regulatory sensitivity.

A further implication is that implementation should be staged. Figure 2 proposes an adaptive governance cycle: diagnose the decision problem; prioritize options using value and risk criteria; pilot under controlled conditions; govern through model, conduct, and cyber controls; then scale, redesign, or exit. Each stage produces evidence that updates the next decision. This approach responds directly to the literature on algorithm aversion, transparency, and performance heterogeneity: a pilot is not merely a technical test but an experiment in customer behavior, operational resilience, and governance quality.

For Saudi Arabia, contextualization should occur through weights and constraints rather than through unsupported assumptions that the market is exceptional. Existing studies justify attention to policy intervention, usefulness, trust, open-banking experience, and digital-finance ethics (Al-Baity, 2023; Ansari & Bansal, 2024; Mutambik, 2023). However, brokerage-specific empirical calibration is still missing. The proposed framework is therefore best viewed as a testable decision architecture, not a validated Saudi scoring formula.

The integrated architecture can also be interpreted through the distinction between efficiency and legitimacy. Efficiency concerns whether technology reduces time, error, or cost and improves forecasting or service capacity. Legitimacy concerns whether customers, employees, regulators, and governance bodies regard the decision process as understandable, fair, and accountable. Brokerage transformation fails when either side is ignored. A highly legitimate but inefficient process may be commercially unsustainable, while a highly efficient but opaque process may face low usage, complaints, supervisory intervention, or reputational damage. Advanced models should therefore include indicators from both categories and avoid translating every consideration into a single financial value.

Sensitivity analysis becomes particularly important when strategic priorities are contested. Management may emphasize growth and cost efficiency; compliance may emphasize explainability and conduct risk; technology teams may emphasize scalability and architecture; clients may emphasize convenience, control, and confidence. A useful governance process should show how rankings change across those stakeholder perspectives. If one option remains preferred under diverse plausible weights, the decision is robust. If rankings reverse, the disagreement is substantive and should be surfaced rather than averaged away. This practice turns MCDA into a mechanism for transparent organizational debate rather than a device for producing an apparently precise score.

For empirical application, each criterion should also have a defined measurement scale, data owner, update frequency, and decision threshold. This prevents broad

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723547

concepts such as trust, resilience, or explainability from becoming rhetorical labels. A criterion should influence ranking only when the organization can specify what evidence changes its value and who is accountable for validating that evidence. This discipline improves comparability across projects and creates an auditable record of why priorities changed over time. The same principle applies to benefits. Revenue uplift, faster onboarding, lower manual effort, better advice, and improved surveillance should not be accepted as self-evident outcomes. Each claim requires a baseline, an observation window, an attribution rule, and a confidence range. Where benefits depend on customer migration or advisor adoption, the model should include behavioral assumptions and test them during the pilot. Where benefits depend on future scale, capacity limits and variable operating costs should be visible. This converts the business case from a promotional estimate into a falsifiable decision hypothesis. Governance can then compare expected and realized value at predetermined review points. A project that misses its benefits but remains safe may be redesigned; a project that creates value while breaching control thresholds should be constrained or suspended. This separation between value evidence and control evidence is important because it prevents commercial success from normalizing unacceptable risk. It also helps boards and regulators understand the basis for continuation decisions.

In addition, criteria should be time-sensitive. Cyber exposure, vendor concentration, market volatility, customer preferences, and model accuracy can change after deployment, so yesterday's ranking should not become a permanent entitlement to capital. Periodic reassessment should refresh weights, scenarios, and thresholds using the latest operational evidence. By documenting these revisions, firms can distinguish genuine learning from opportunistic re-scoring designed to protect favored projects. The resulting record supports institutional memory and allows later reviewers to reconstruct how a transformation decision evolved from initial proposal to scale, redesign, or exit. Independent assurance can strengthen this process by testing data lineage, validation evidence, override behavior, and vendor controls before major scale decisions, especially where automated recommendations directly affect client portfolios or market conduct. Accordingly, the final model should state evidence requirements explicitly.

Table 2. Decision-model families and their recommended roles

Model family	Primary role	Strength	Key limitation	Recommended brokerage use
AHP / ANP	Elicit criteria weights and dependencies	Transparent stakeholder structuring	Subjective judgments; rank sensitivity	Strategic prioritization and governance-weight elicitation
TOPSIS / VIKOR	Rank alternatives against ideal or compromise solutions	Clear comparative ranking	Compensatory logic can mask veto risks	Technology and vendor shortlisting after risk gates
Scenario / stress analysis	Test outcomes under uncertain future states	Reveals fragility and downside exposure	Depends on scenario quality	Market, regulatory, cyber, and adoption stress testing
Predictive analytics / ML	Estimate demand, risk, performance, and operational impact	Data-driven updating and pattern detection	Drift, bias, opacity, data dependence	Forecasting and monitoring within governed workflows
Bayesian / real-options logic	Update beliefs and value staged investments	Supports learning and reversibility	More demanding assumptions and calibration	Pilot-to-scale decisions and uncertain platform investments
Hybrid governance model	Combine algorithmic ranking with human review and vetoes	Balances scale with accountability	Potential delays and inconsistent overrides	High-impact suitability, advisory, surveillance, and exception decisions

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723547

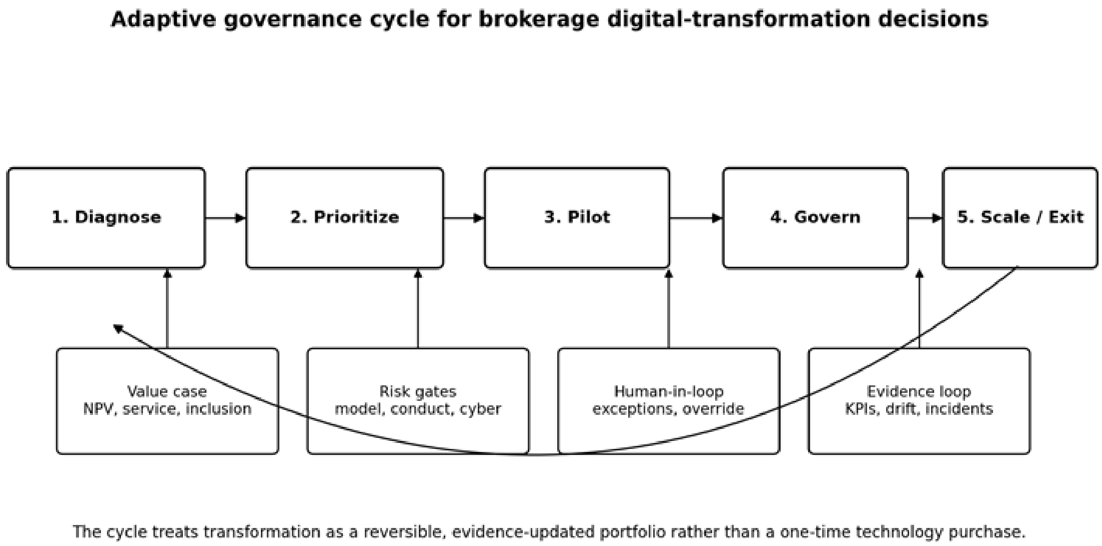

Figure 2. Adaptive governance cycle for brokerage digital-transformation decisions.

The cycle operationalizes Figure 1 by converting model outputs into staged, reversible investment and governance decisions.

VIII. RESEARCH GAPS AND FUTURE RESEARCH

The largest gap is the absence of Saudi brokerage-specific comparative evidence. Future studies should collect firm-level and client-level data linking digital initiatives to execution quality, account activation, complaint rates, suitability outcomes, advisor productivity, cyber incidents, and cost-to-serve. Such data would permit estimation of criterion weights from observed outcomes rather than managerial judgment alone.

Second, research should compare decision-model families. AHP-TOPSIS, ANP-VIKOR, outranking methods, Bayesian decision models, real-options analysis, and robust portfolio optimization may produce different rankings under the same evidence. Comparative studies should examine stability, interpretability, data requirements, and governance burden. Third, explainability research should move beyond generic transparency and test Arabic-language explanations, visual risk communication, and explanations tailored to investor sophistication. Fourth, hybrid human–algorithm models require causal evidence on when human review adds value and when it merely adds delay or inconsistent discretion.

Fifth, future work should integrate model risk with strategic value over time. Most adoption research is cross-sectional, whereas brokerage transformation unfolds through learning, drift, market shocks, and regulatory change. Longitudinal studies could test whether initial trust survives model error and whether governance interventions restore usage. Finally, Shariah-sensitive decision criteria should be operationalized carefully through collaboration among finance scholars, Shariah specialists, regulators, and practitioners rather than assumed from generic Islamic-finance labels. The goal should be measurable decision rules that can be audited within digital workflows.

A further opportunity is to study transformation as a network of dependent decisions. Most research evaluates a single technology or adoption intention, yet brokerage initiatives share data, controls, channels, and employees. Future studies could use network models or portfolio optimization to estimate complementarities and bottlenecks among digital identity, customer data platforms, AI research tools, surveillance, advisory automation, and cloud modernization. Such work would help determine optimal sequencing, not just the attractiveness of isolated projects. Researchers should also investigate failure and exit decisions. Publishing only successful pilots creates survivorship bias and gives managers little guidance on when to stop a technology that remains technically functional but economically or institutionally weak. Evidence on rollback, vendor replacement, and de-automation would make the field more realistic.

IX. PRACTICAL, MANAGERIAL AND POLICY IMPLICATIONS

For brokerage executives, the principal implication is to establish a transformation investment committee that uses a documented decision model instead of isolated technology business cases. Candidate initiatives should be scored on financial value, client value, operational durability, data readiness, integration complexity, explainability, cyber risk, regulatory traceability, and workforce capability. High uncertainty should trigger a pilot rather than an inflated risk premium hidden inside a spreadsheet.

For technology and operations managers, the framework encourages modular architecture. APIs, common data definitions, identity controls, model registries, and monitoring services increase the option value of later initiatives by reducing switching costs and improving observability. For risk and compliance functions, define governance criteria before procurement: required explanations, audit records, validation thresholds, human override rules, incident escalation, third-party obligations, and exit arrangements.

To policymakers and market supervisors, a useful direction is outcome-based guidance that specifies accountability, suitability, transparency, resilience, and data-protection expectations while allowing firms flexibility in technical implementation. Regulatory experimentation can be most valuable when it produces evidence about control effectiveness, not simply faster licensing. Industry-wide taxonomies for model incidents and automated-advice complaints could also improve benchmarking. Finally, investor education should be treated as part of market infrastructure because the literature consistently links comprehension, perceived value, and trust to adoption and effective use.

X. LIMITATIONS

This review has four limitations. First, it synthesizes adjacent banking and robo-advisory evidence because peer-reviewed research focused specifically on Saudi brokerage operations is sparse. Transferability is therefore analytical rather than statistical. Second, the field changes rapidly; models, regulation, and platform designs can evolve faster than publication cycles. Third, the review emphasizes peer-reviewed English-language literature from 2020–2025 and may omit relevant earlier or Arabic scholarship. Fourth, the proposed decision architecture has not yet been calibrated or validated with proprietary brokerage data. Its value lies in organizing testable criteria and governance logic, not in claiming proven performance superiority.

XI. CONCLUSION

Digital transformation of brokerage operations is best understood as a repeated choice among competing sociotechnical configurations. Recent evidence shows that AI, automation, robo-advisory, and digital platforms can improve scale, analytical consistency, access, and service efficiency, but the same technologies create challenges in trust, privacy, explanation, accountability, and behavioral acceptance. Saudi studies reinforce the importance of usefulness, policy support, customer experience, and institutional trust. Accordingly, advanced decision-making should integrate multi-criteria prioritization with predictive analytics, scenarios, hard governance constraints, and post-deployment learning.

The proposed framework shifts managerial attention from acquiring technologies to governing a transformation portfolio. It distinguishes rankable benefits from non-negotiable controls, evaluates fully automated and hybrid models separately, and uses pilots as evidence-generating mechanisms. This makes digital strategy more adaptive: initiatives can be scaled when value and control are demonstrated, redesigned when uncertainty remains material, and exited when risks dominate. The immediate research priority is empirical validation in Saudi brokerage firms using longitudinal operational and customer data. Until such evidence exists, the most defensible approach is not maximal automation but transparent, measurable, and reversible decision-making in which technology, human judgment, and regulation are designed as one system.

REFERENCES

[1] S. Ahmed, M. M. Alshater, A. El Ammari, and H. Hammami, "Artificial intelligence and machine learning in finance: A bibliometric review," *Research in International Business and Finance*, vol. 61, Art. no. 101646, 2022. ScienceDirect

[2] H. H. Al-Baity, "The artificial intelligence revolution in digital finance in Saudi Arabia: A comprehensive review and proposed framework," *Sustainability*, vol. 15, no. 18, Art. no. 13725, 2023. MDPI

[3] H. A. Alnemer, "Determinants of digital banking adoption in the Kingdom of Saudi Arabia: A technology acceptance model approach," *Digital Business*, vol. 2, no. 2, Art. no. 100037, 2022. ScienceDirect

[4] Y. Ansari and R. Bansal, "Robo-advisory financial services and the dynamics of new innovation in Saudi Arabia," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 10, no. 4, Art. no. 100397, 2024. ScienceDirect

[5] M. Arenas-Parra, H. Rico-Pérez, and R. Quiroga-Garcia, "The emerging field of Robo Advisor: A relational analysis," *Heliyon*, vol. 10, no. 16, Art. no. e35946, 2024. ScienceDirect

[6] E. C.-X. Aw, L.-Y. Leong, J.-J. Hew, N. P. Rana, T. M. Tan, and T.-W. Jee, "Counteracting dark sides of robo-advisors: Justice, privacy and intrusion considerations," *International Journal of Bank Marketing*, vol. 42, no. 1, pp. 133–151, 2024. Emerald

[7] C. Back, S. Morana, and M. Spann, "When do robo-advisors make us better investors? The impact of social design elements on investor behavior," *Journal of Behavioral and Experimental Economics*, vol. 103, Art. no. 101984, 2023. ScienceDirect

[8] D. Barile, G. Secundo, and C. Bussoli, "Exploring artificial intelligence robo-advisor in banking industry: A platform model," *Management Decision*, vol. 63, no. 10, pp. 3323–3349, 2025. Emerald

[9] D. Belanche, L. V. Casaló, M. Flavián, and S. M. C. Loureiro, "Benefit versus risk: A behavioral model for using robo-advisors," *The Service Industries Journal*, vol. 45, no. 1, pp. 132–159, 2025. Taylor & Francis

[10] A. Bhatia, A. Chandani, R. Atiq, M. Mehta, and R. Divekar, "Artificial intelligence in financial services: A qualitative research to discover robo-advisory services," *Qualitative Research in Financial Markets*, vol. 13, no. 5, pp. 632–654, 2021. Emerald

[11] G. Cohen, "Algorithmic trading and financial forecasting using advanced artificial intelligence methodologies," *Mathematics*, vol. 10, no. 18, Art. no. 3302, 2022. MDPI

[12] C. Digmayer, "Automated economic welfare for everyone? Examining barriers to adopting robo-advisors from the perspective of explainable artificial intelligence," *Journal of Interdisciplinary Economics*, vol. 36, no. 2, pp. 224–245, 2024. SAGE

[13] K. S. Eichler and E. Schwab, "Evaluating robo-advisors through behavioral finance: A critical review of technology potential, rationality, and investor expectations," *Frontiers in Behavioral Economics*, vol. 3, Art. no. 1489159, 2024. Frontiers

[14] O. H. Fares, I. Butt, and S. H. M. Lee, "Utilization of artificial intelligence in the banking sector: A systematic literature review," *Journal of Financial Services Marketing*, vol. 28, no. 4, pp. 835–852, 2022.

[15] Filiz, J. R. Judek, M. Lorenz, and M. Spiwoks, "Algorithm aversion as an obstacle in the establishment of robo advisors," *Journal of Risk and Financial Management*, vol. 15, no. 8, Art. no. 353, 2022. MDPI

[16] R. M. Gaspar and M. Oliveira, "Robo advising and investor profiling," *FinTech*, vol. 3, no. 1, pp. 102–115, 2024. MDPI

[17] A. Grealish and P. N. Kolm, "Robo-advisors today and tomorrow: Investment advice is just an app away," *The Journal of Wealth Management*, vol. 24, no. 3, pp. 144–155, 2021. Journal of Wealth Management

[18] N. Helms, R. Hölscher, and M. Nelde, "Automated investment management: Comparing the design and performance of international robo-managers," *European Financial Management*, vol. 28, no. 4, pp. 1028–1078, 2022. Wiley

[19] K. Hentzen, A. Hoffmann, R. Dolan, and E. Pala, "Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research," *International Journal of Bank Marketing*, vol. 40, no. 6, pp. 1299–1336, 2022. Emerald

[20] H. Herrmann and B. Masawi, "Three and a half decades of artificial intelligence in banking, financial services, and insurance: A systematic evolutionary review," *Strategic Change*, vol. 31, no. 6, pp. 549–569, 2022. Wiley

[21] X. Hong, L. Pan, Y. Gong, and Q. Chen, "Robo-advisors and investment intention: A perspective of value-based adoption," *Information & Management*, vol. 60, no. 6, Art. no. 103832, 2023. ScienceDirect

[22] Kumar, "Evolution of financial advisory market with the advent of robo-advisors," *Managerial Finance*, vol. 51, no. 5, pp. 831–856, 2025. Emerald

[23] P. Marano and S. Li, "Regulating robo-advisors in insurance distribution: Lessons from the Insurance Distribution Directive and the AI Act," *Risks*, vol. 11, no. 1, Art. no. 12, 2023. MDPI

[24] Mutambik, "Customer experience in open banking and how it affects loyalty intention: A study from Saudi Arabia," *Sustainability*, vol. 15, no. 14, Art. no. 10867, 2023. MDPI

[25] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, Art. no. n71, 2021. BMJ

[26] R. K. Singh, R. Mishra, S. Kumar, and S. Bag, "Applications of artificial intelligence for optimizing banking and financial operations: A systematic literature review and future research agenda," *Journal of Economic Surveys*, vol. 39, no. 5, pp. 2284–2302, 2025. Wiley

[27] M. K. P. So, "Robo-advising risk profiling through content analysis for sustainable development in the Hong Kong financial market," *Sustainability*, vol. 13, no. 3, Art. no. 1306, 2021. MDPI

[28] Q. Yang and Y.-C. Lee, "Enhancing financial advisory services with GenAI: Consumer perceptions and attitudes through service-dominant logic and artificial intelligence device use acceptance perspectives," *Journal of Risk and Financial Management*, vol. 17, no. 10, Art. no. 470, 2024. MDPI

[29] H. Zhu, E. S. Pysander, and I. Söderberg, "Not transparent and incomprehensible: A qualitative user study of an AI-empowered financial advisory system," *Data and Information Management*, vol. 7, no. 3, Art. no. 100041, 2023. ScienceDirect

[30] H. Zhu, O. Vigren, and I. Söderberg, "Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda," *Journal of Business Research*, vol. 174, Art. no. 114494, 2024. ScienceDirect