

Leveraging Robo-Advisory Technology for Sustainable Financial Inclusion: A Structural Analysis

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Abstract

Robo-advisors, or algorithmically driven digital platforms that provide automated financial advising services, are drastically changing the world of wealth management. Although these technologically advanced financial solutions have become increasingly popular in industrialised financial systems, their incorporation in emerging countries is still comparatively restricted and fundamentally unexplored. By using expert elicitation to identify sixteen interdependent Critical Success Factors (CSFs), this study methodically examines the major structural factors driving the adoption of robo-advisory services. The study uses Interpretive Structural Modelling (ISM) in conjunction with MICMAC analysis to investigate the intricate interactions between these components, allowing for the creation of a hierarchical, multi-level framework. The results show that the effective deployment of robo-advisory platforms is shaped by profound systemic interdependencies. Regulatory compliance, algorithmic transparency, data security, and financial literacy stand out as high-driving power elements that have a big impact on the adoption ecosystem as a whole. Conversely, these structural drivers appear to shape dependent outcomes including customer trust, institutional readiness, affordability, and technological innovation. The suggested ISM–MICMAC paradigm goes beyond conventional individual-centric technology adoption frameworks by providing an organised system-level perspective and emphasising the significance of institutional, regulatory, and infrastructure dynamics. Policymakers, financial institutions, and technology developers can use the study's strategic insights to create robust, scalable, and sustainable robo-advisory solutions that can handle the particular difficulties and opportunities found in developing financial markets.

Introduction

Financial technology (FinTech) innovations are rapidly transforming traditional financial services. A notable example is the robo-advisor – an algorithm-driven platform that provides automated investment advice and portfolio management with minimal human intervention. As described by Arenas-Parra et al. (2024), robo-advisors aim to 'popularize investment advisory services by automating all the activities involved.' Likewise, market analysis estimate that the robo-advisory industry (in terms of revenues or assets) grew from about USD 6.36 billion in 2023 to USD 8.01 billion in 2024 and is forecast to reach over USD 33 billion by 2030 (Size, 2023). This surge reflects accelerating demand for convenient, low-cost digital investment services worldwide. While robo-advisors have proliferated in advanced economies, their growth in emerging markets is still nascent but holds great promise (Gomber et al., 2017). In emerging markets, underserved populations include about 1.6 billion adults and 200 million small businesses that lack access to formal financial services (Demirguc-Kunt et al., 2018). FinTech companies – including online lenders, payment platforms and now robo-advisors – have begun to tap this unmet demand by leveraging innovations in mobile connectivity and data analytics (Óskarsdóttir et al., 2019). In this context, identifying critical success factors (CSFs) for robo-advisors becomes essential. CSFs are the key areas that must go well for an organization or project to succeed. The success of a robo-advisory service will depend on multiple interrelated elements: e.g. algorithm accuracy, user interface design, brand reputation, data security, local compliance, and customer education (Dellaert et al., 2024). These factors are especially salient in emerging markets, where issues like limited internet penetration, unfamiliarity with automated advice, and evolving regulatory regimes can pose unique challenges. Understanding which CSFs most impact robo-advisor adoption and performance in the emerging markets will help investors, technology providers, and policymakers allocate resources effectively and address potential barriers. The extensive literature review has uncovered the following research gaps:

- While existing studies have extensively examined individual adoption drivers of robo-advisors such as trust, ease of use, and usefulness these investigations are almost entirely confined to advanced economies. Emerging markets like India, where robo-advisor penetration remains below 5%, lack focused research on the full spectrum of critical success factors influencing market entry and growth.
- The bulk of fintech adoption research relies on survey-based frameworks (e.g., TAM, UTAUT) and regression analysis. As a result, interactions among multiple success factors spanning regulatory compliance, technological readiness, product innovation, and algorithm transparency remain unexplored in the Indian context.
- Although multi-criteria methods such as fuzzy DEMATEL have mapped cause–effect links among fintech CSFs, none have offered a structured, hierarchical model that captures the driving and dependent power of factors. ISM-MICMAC techniques, proven effective in other domains for revealing factor hierarchies and interdependencies, have not been applied to robo-advisor CSF analysis.
- There is no expert-validated framework that synthesizes and ranks critical success factors for robo-advisors in India’s unique financial ecosystem. This gap underscores the need for an ISM-MICMAC study to develop a rigorous, stakeholder-endorsed model guiding strategic decision-making.

Therefore, the current study aims to bridge these gaps by identifying and evaluating the critical success factors for robo-advisors in emerging financial markets and develop an ISM -based hierarchical model to see how these CSFs are affecting each other, and further MICMAC analysis is used to classify each factor by its driving and dependence power into cause, effect and mediator factor. For this purpose, the study has framed research questions which are as follows:

Q1. What are the critical success factors (CSFs) influencing the adoption of robo-advisors in emerging financial markets?

Q2. How can these CSFs be hierarchically structured based on their driving and dependence power using the ISM approach?

Q3. What interrelationships exist among these CSFs as revealed by the MICMAC analysis?

The structure of the present study is outlined as follows: Section 2 reviews the relevant literature, focusing on the critical success factors influencing the robo advisors in the emerging markets. Section 3 explains the research methodology employed, followed by Section 4, which details the development process and procedural steps of the ISM approach. Section 5 illustrates the MICMAC analysis and presents the final ISM model. Finally, Section 6 discusses the key findings, outlines the study’s limitations, and suggests directions for future research.

2. Literature Review

The exponential use of technology in the financial markets has attracted the attention of the researchers. They are keen in exploring the factors affecting the use of robo-advisors in the financial markets. Numerous studies slated the factors affecting the use of robo-advisors in the field of sales, marketing and finance. Through the literature review, the study has recognized 20 variables that affect the use of robo- advisor in the financial markets. These variables are shown in the Appendix 1 and discussed in the upcoming sections.

2.1 Technological Infrastructure (CSF1)

D'Acunto, Prabhala, and Rossi (2019) show that cloud-native implementations reduce infrastructure capital expenditure and shorten time-to-market for advanced machine-learning models, while also facilitating continuous integration pipelines for third-party data feeds via standardized RESTful APIs (D'Acunto et al., 2019). In emerging markets like India, regulatory frameworks (e.g., RBI's digital-lending sandbox) and payment infrastructures (UPI) offer a foundation for fintech integration, but gaps in API standardization and data localization rules persist (Reserve Bank of India, 2021). Addressing these gaps requires strategic public-private partnerships to expand edge-computing nodes and bolster network resilience in underserved regions, ensuring consistently low latency for mobile-first users (Jagtiani & Lemieux, 2017). Finally, interoperability with banking and custodial systems via well-documented APIs is critical for end-to-end automation of KYC/AML processes and seamless fund flows (Buckley et al., 2023). Thus, technological infrastructure is not merely an operational necessity but a strategic enabler that shapes both the functional performance and the perceived legitimacy of robo-advisor offerings in emerging financial markets.

2.2. Perceived Trust

Empirical studies on robo-advisors underscore the multifaceted nature of trust. D'Acunto, Prabhala, and Rossi (2019) found that platforms emphasizing transparent algorithmic logic and regulatory compliance enjoyed higher user retention, suggesting that perceived procedural fairness and accountability bolster confidence in automated advice (D'Acunto et al., 2019). Similarly, Huang and Rust (2021) argue that “explainable AI” features—such as visual risk dashboards and plain-language justifications for portfolio shifts—mitigate the “black-box” effect, strengthening users’ affective trust in the system’s recommendations (Huang & Rust, 2021). In emerging markets like India, where fintech literacy varies widely, institutional trust cues assume greater importance. By combining explainable algorithms, robust security certifications, and culturally attuned trust signals, firms can effectively address users’ uncertainty and drive wider acceptance in emerging financial markets.

2.3. Perceived Usefulness

In emerging markets, where financial literacy and trust in digital platforms may be lower, usefulness signals play an even greater role. Mahmud and Joarder (2022) show in a large-scale survey of Southeast Asian investors that perceived usefulness mediates the relationship between platform credibility and adoption intention, indicating that credibility alone is insufficient without clear demonstrations of performance enhancements (Mahmud et al., 2022). Similarly, Lee and Shin (2018) highlight that integration of predictive analytics and personalized recommendations increases users’ perceived usefulness, leading to higher willingness to adopt automated advice (Lee & Shin, 2018). Given these insights, robo-advisor providers should prioritize user interfaces that emphasize key performance indicators—historical returns relative to benchmarks, tax-loss harvesting benefits, and automated rebalancing schedules—to bolster perceived usefulness. Moreover, tailoring communication to local investment goals (e.g., retirement planning versus wealth accumulation) can enhance relevance and thus usefulness perceptions (Venkatesh et al., 2012). By foregrounding concrete value propositions, firms can leverage perceived usefulness to drive initial adoption and foster long-term engagement in emerging financial markets.

2.4. Willingness to Adopt

“Willingness to adopt” reflects an individual’s intention to start using a new technology and is often operationalized as behavioral intention in diffusion and acceptance models (Rogers, 2003). In fintech settings, the design of robo-advisor interfaces and transparency of outcomes directly influence users’ adoption willingness. Their field experiment found that participants exposed to interactive performance dashboards—highlighting simulated returns versus benchmarks—reported significantly higher intention to allocate real funds, underscoring the role of clear

outcome visualizations in fostering adoption (D'Acunto et al., 2019). A recent systematic review of Financial Robo-Advisors (FRAs) confirms that users who perceive tangible benefits in cost savings, portfolio diversification, and 24/7 access exhibit stronger willingness to adopt automated advice (Nourallah et al., 2025). Collectively, these studies highlight that “willingness to adopt” robo-advisors depends not only on individual perceptions of usefulness and ease but also on interface transparency, explanatory features, and the broader infrastructural and regulatory environment.

2.5. Awareness and Understanding

Awareness and understanding constitute the foundational “knowledge” stage in the diffusion of innovations, in which potential adopters first learn of an innovation’s existence and gain some comprehension of how it functions. Without sufficient awareness—both service and of its underlying mechanics—users cannot form judgments about its usefulness, risks, or relevance to their needs, stalling any further progression toward adoption. Beyond mere exposure, technology readiness—the propensity to embrace and use new technologies—mediates how well awareness translates into understanding. Users scoring high on the Technology Readiness Index (TRI) more quickly move from recognition to functional understanding because they actively seek information, experiment with demos, and interpret technical jargon correctly (Abhijith & Bijulal, 2020). Conversely, those with low TRI may remain aware yet fail to understand, perceiving the service as “black-box” and thus resisting further exploration (Parasuraman, 2000).

2.6. Financial Inclusion

Financial inclusion broadening access to affordable, appropriate financial services for underserved populations is widely recognized as a key driver of economic development and poverty reduction. Ozili (2018) shows that digital finance platforms can cut per-transaction costs by up to 80% compared to traditional channels, enabling robo-advisors to offer management fees as low as 0.25% annually levels unattainable by brick-and-mortar advisory firms (Ozili, 2018). Frost et al. (2019) further argue that leveraging cloud computing and automated processes allows robo-advisors to scale rapidly across regions, reducing fixed-cost barriers and facilitating micro-investment products that bundle small, diversified portfolios for low-income users (Frost et al., 2019). In many emerging economies, mobile phones are the primary gateway to financial services. Suri and Jack (2016) document how mobile-money platforms in Kenya raised household savings and lifted 2% of families out of poverty by enabling small-value transactions. Analogously, mobile-first robo-advisor apps that integrate with mobile-money wallets can let users in remote areas open, fund, and monitor investment accounts without bank branches or desktop computers (Suri & Jack, 2016). Beyond transactional access, robo-advisors often embed educational modules interactive tutorials, goal-setting tools, and risk-profiling questionnaires that enhance financial literacy.

2.7 Customer Financial Literacy

The combination of knowledge, skills, and confidence to make effective financial decisions has been shown to be a strong predictor of individuals’ engagement with complex financial products, including robo-advisory services. Lusardi and Mitchell (2014) demonstrate that higher financial literacy is associated with greater retirement planning and investment participation, implying that literate users are more likely to comprehend and trust algorithmic portfolio management (Lusardi & Mitchell, 2014). Similarly, van Rooij, Lusardi, and Alessie (2011) find that households scoring in the top quartile of financial literacy are twice as likely to participate in stock markets compared to those in the bottom quartile, underscoring the role of foundational knowledge in adopting digital investment platforms (Van Rooij et al., 2011). Finally, Xiao and O’Neill (2014) find that higher financial capability an outcome of literacy correlates with greater financial satisfaction and resilience, suggesting that literate robo-advisor

users not only adopt but also remain with platforms longer when they perceive personal financial well-being gains (Xiao et al., 2014). Taken together, this body of research indicates that customer financial literacy is a critical enabler of robo-advisor uptake: providers must assess and elevate users' knowledge through integrated educational features to foster informed adoption and sustained engagement.

2.8 Reliable Customer Service

In mobile financial services, Koenig-Lewis, Palmer, and Moll (2010) note that reliability of app performance minimal crashes and accurate balance updates significantly elevates users' willingness to engage with digital channels. (Koenig-Lewis et al., 2010) extend this by demonstrating that reliability interplays with responsiveness: customers perceive service as more reliable when support teams resolve queries within stringent timeframes, reinforcing perceptions of competence (McKelvey et al., 2021). In robo-advisory specifically, where algorithmic recommendations must be backed by clear escalation paths for exceptions (e.g., margin calls, technical errors), service reliability entails well-designed fallback protocols and human-in-the-loop interventions (Yang & Fang, 2004).

2.9. Investment Performance

Machine-learning approaches represent the latest evolution. Wang and Yu (2021) introduce an inverse-optimization plus deep-reinforcement-learning pipeline that back-tests to a 12% cumulative outperformance over the S&P 500 from 2016 to 2021 (Wang & Yu, 2021). Liu, Yang, and Wen (2023) examine the COVID-19 crisis, finding that robo-advisor clients experienced drawdowns approximately 30% smaller than matched self-directed investors, highlighting the risk-management advantages of algorithmic discipline (Liu et al., 2023). Lastly, real-world evaluations corroborate academic work. D'Hondt, De Winne, Ghysels, and Raymond (2020) find that when robo-advisors incorporate simple anthropomorphic cues, user adherence to algorithmic advice increases, indirectly boosting net returns by up to 3% annually. Collectively, these studies confirm that through disciplined rebalancing, robust heuristic allocations, factor-tilted strategies, and emerging AI-driven personalization, robo-advisors deliver competitive, risk-adjusted performance particularly in volatile markets making investment performance a critical success factor in emerging financial markets (D'Hondt et al., 2020).

2.10 Customer Relationship Management

Customer Relationship Management (CRM) is the set of processes, practices, and technologies that firms employ to manage and analyze customer interactions throughout the customer lifecycle, with the goal of improving retention and driving sales growth. In the digital wealth-management space, effective CRM systems enable robo-advisor platforms to deliver personalized advice, automated lifecycle communications, and proactive service interventions at scale, thereby fostering long-term client engagement (Buttle & Maklan, 2019). Customer engagement customers' cognitive, emotional, and behavioral investment in specific firm offerings extends CRM's traditional focus on transactions to include interactive touchpoints. Verhoef, Reinartz, and Krafft (2010) develop a customer engagement framework that underscores the importance of multi-channel, personalized interactions in building brand evangelism and advocacy. For robo-advisors, such engagement can take the form of in-app educational content, goal-tracking nudges, and timely market insights (Verhoef et al., 2010).

2.11. Data Privacy Compliance

Data privacy compliance adhering to legal and ethical standards for collecting, processing, and storing personal information is fundamental for robo-advisor platforms that manage sensitive financial and behavioral data. Early research on privacy concerns laid the groundwork for understanding users' demands for control and transparency. Romanosky, Telang, and Acquisti (2011) show that breach-disclosure laws, by requiring firms to notify affected

individuals, reduce identity-theft rates and motivate stronger security investments (Romanosky et al., 2011). Economic analyses highlight the stakes: Acquisti, Taylor, and Wagman (2016) estimate that post-breach stock prices drop by an average of 3% and customer churn can exceed 15%, underscoring the financial imperative for robust compliance (Acquisti et al., 2016). Zarsky (2016) extends this to algorithmic systems, warning that opaque AI models risk “inadvertent inference” of sensitive traits unless designed with explainability and differential-privacy techniques (Zarsky, 2016).

2.12. Transparent Communication

Transparent communication defined as the clear, timely, and honest sharing of information between firms and stakeholders builds credibility, reduces uncertainty, and fosters trust in digital financial services. In the robo-advisor context, transparency involves disclosing algorithmic methodologies, fee structures, performance metrics, and data-usage policies in accessible formats, enabling investors to make informed decisions and feel confident delegating portfolio management tasks (Rawlins, 2008). Information-quality scholarship underlines the importance of clarity and relevance. Eppler and Wittig (2000) propose that high-quality information is accurate, complete, and comprehensible qualities essential for robo-advisor disclosures, which must explain complex portfolio-construction rules in lay terms (Eppler & Wittig, 2000). Effective transparency extends to policy communication. Milne and Culnan (2004) demonstrate that layered “privacy nutrition labels” and summary notices greatly increase users’ comprehension of privacy practices compared to lengthy legal texts, suggesting best practices for robo-advisor data-usage disclosures (Milne & Culnan, 2004). Rawlins (2008) emphasizes that two-way transparency inviting stakeholder feedback and responding promptly strengthens relational trust and signals firm responsiveness (Rawlins, 2008). Collectively, this literature underscores that transparent communication through clear algorithmic explanations, straightforward fee disclosures, high-quality information, and interactive policy summaries is a critical success factor for robo-advisors aiming to build and maintain investor trust in emerging financial markets.

2.13. Low Cost

Low operational and management costs constitute a fundamental value proposition of robo-advisor platforms, enabling access to automated investment advice at fees far below those charged by traditional human advisors. Authors show that perceived fee advantage significantly drives customer adoption of robo-advisors, with platforms offering annual management fees below 0.50% attracting cost-sensitive retail investors (Belanche et al., 2019). Digital entry-level products also contribute to cost efficiency. Ozili (2018) documents that fintech platforms including robo-advisors cut transaction and account-maintenance costs by up to 80% through paperless processes and straight-through processing, making micro-investment products viable for small-balance clients who would otherwise be unprofitable under legacy pricing models (Ozili, 2018). Researchers observe that this “unit-cost revolution” enables robo-advisors to democratize portfolio management, with some firms offering fully automated advisory services for fees as low as 0.15% per annum once certain AUM tiers are reached (Sahay et al., 2020). Collectively, these studies confirm that automation, scale economies, streamlined processes, and cost-efficient portfolio rules underpin the low-cost advantage of robo-advisors, making “Low Cost” a pivotal critical success factor in emerging financial markets.

2.14. Efficient Rebalancing

Efficient rebalancing the systematic adjustment of portfolio weights to maintain target allocations ensures that robo-advisors capture intended risk–return profiles while minimizing transaction costs and drift from strategic asset mixes. Emerging research explores transaction-cost optimization through graph-based pathfinding: Vallarino (2024) integrates graph neural networks to predict trade costs and uses shortest-path algorithms to execute multi-

leg rebalances at minimal expense, yielding 15% lower trading friction in high-velocity environments (Vallarino, 2024). Collectively, these studies affirm that efficient rebalancing combining appropriate frequency or drift-based triggers, cost-sensitive trade execution, and adaptive rule refinement is vital for robo-advisor platforms seeking to deliver consistent, risk-adjusted performance in emerging financial markets.

2.15. Hybrid Human Support

Hybrid human support in robo-advisory refers to the integration of automated algorithms with human financial advisors to enhance service delivery. This model aims to combine the efficiency and scalability of technology with the trust, personalization, and emotional intelligence offered by human advisors (Sironi, 2016). In emerging markets where digital literacy, financial literacy, and trust in technology may be inconsistent the hybrid model has been particularly relevant in improving adoption and satisfaction with robo-advisory platforms. Empirical research indicates that users value the option to speak with a human when financial decisions involve complexity or uncertainty. For instance, Jung et al. (2018) found that hybrid robo-advisors, such as those offered by Vanguard's Personal Advisor Services and Schwab Intelligent Portfolios, have significantly higher user satisfaction and retention rates compared to purely algorithmic platforms. Hybrid robo-advisory is also linked to broader digital inclusion. Suryono et al. (2020) observed in Indonesia that hybrid platforms reduce the digital divide by offering telephonic and video call support in regional languages, improving adoption among older and rural populations (Suryono et al., 2020). In emerging markets, where financial ecosystems are still maturing, the hybrid model serves as a transitional interface building investor confidence while nudging users toward fully digital solutions. Future studies are likely to focus on how to optimize the division of labor between humans and machines, how hybrid models affect cost structures, and their role in financial well-being outcomes.

2.16. Local Language Support

Local language support plays a pivotal role in enhancing the accessibility, usability, and trust in financial technologies, particularly in multilingual and culturally diverse emerging markets. Robo-advisors, which rely on digital interfaces to guide users through investment decisions, must ensure that their platforms are linguistically inclusive to reach a broader population base and promote financial inclusion. In emerging economies like India, where English proficiency remains limited among large segments of the population, digital financial services in local languages significantly improve user adoption and comprehension (Kandpal & Mehrotra, 2019). Language not only enables better understanding of financial products but also builds emotional resonance and perceived trust, especially among first-time or less tech-savvy investors (Gomber et al., 2018). Finally, multilingual platforms show increased user retention and reduced dropout rates (Suri & Jack, 2016). Therefore, local language support emerges not merely as a cosmetic addition but as a critical success factor that ensures inclusivity, drives adoption, and supports long-term engagement.

Methodology

This section comprises two primary phases. Initially, essential success variables have been examined by a comprehensive literature analysis and insights from experts. Secondly, employed the Interpretative Structural Modelling (ISM)-MICMAC methodology.

3.1 Phase 1

3.1.1 Literature Review and Experts' Opinion

A total of 39 publications pertaining to robo-advisor adoption were examined utilizing several keyword combinations, including Robo-Advisors, Critical Success Factors (CSFs), Financial Technology (FinTech), Digital Investment Platforms, Technology Adoption, Automated Financial Advice, and Financial Inclusion. Out of the 39 papers, 9 were excluded (five were removed due to unrelated material, and four were rejected for lacking adequate information). A total of 30 publications from esteemed journals were included in the study, and 11 experts were consulted to investigate the success elements and collect responses.

3.1.2 Identification of Critical Success Factors

By going through previously available research, The study first identified the most critical success factors to the adoption of robo-advisors. We found 22 crucial factors from 30 publications of high-quality journals. Ultimately, with the support of experts, 16 critical factors were finalised from the list of 22 identified factors by deleting the 6 similar factors. In this study, we contacted 13 experts however 2 denied due to the lack of time and 11 experts from academia and practice, answered and took part in this study. As 5 or above experts are warranted for good decision making, so 11 experts involved in this study are justified.

3.2 Phase 2

3.2.1 ISM

The Interpretative Structural Modelling (ISM) was used for this study. Interpretive Structural Modelling (ISM) is a methodology used to identify and summarize relationships among specific variables associated with a complex issue or system. Developed by Warfield (1973), it facilitates the transformation of poorly structured mental models into a well-organized, hierarchical framework. Through expert judgment, ISM helps to establish contextual relationships among variables, which are then visualized in the form of a directed graph or structural model (Attri et al., 2013). The method is widely applied in areas like decision-making, strategic planning, technology adoption, and systems analysis. Interpretive Structural Modelling (ISM) is a qualitative technique used to convert complex and often ambiguous relationships among variables into a structured, conceptual framework that clarifies their interconnections (Gupta & Sahu, 2013; Sushil, 2012). The resulting model not only aids in systematically analyzing the problem but also offers a clear and logical representation of the system under consideration (Sindhu et al., 2016). ISM follows a redefined structural protocol mentioned as follows:

i. Identification of variables:

Begin by compiling a comprehensive list of factors or variables related to the problem or system under study. These elements are sourced from literature reviews.

ii. Defining Contextual relationship:

Choose a precise contextual relationship that captures how elements interrelate, tailored to the system's interpretive purpose.

iii. Structuring the SSIM (Structural Self-Interaction Matrix):

Pairwise compare each pair of elements, noting directional influences to create the SSIM, a matrix capturing expert judgments by using the following rules-

- Factor i impacts factor j = V

- Factor j impacts factor i = A
- Both the factors i and j impact each other = X
- Both the factors i and j will not impact each other = O

iv. Derivation of the Reachability Matrix:

Convert the SSIM into a binary matrix, applying transitivity rules to capture indirect relationships. This results in a refined reachability matrix.

v. Partitioning levels:

Analyse the reachability and antecedent sets for each element to determine hierarchical levels. Elements with no successors are assigned to the top level, and removed iteratively until all elements are levelled.

vi. Development of the Directed Graph:

Visualize the relationships via a directed graph (digraph), removing transitive links to focus on essential connections. This digraph represents the structural model of the proposed question.

3.2.2 MICMAC

MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) is a technique that helps in validating ISM results and classifying variables into clusters to facilitate policy and managerial implications (Sushil,2012). The purpose of MICMAC analysis is to classify the identified variables into four distinct categories based on their driving power (the ability to influence other variables) and dependence power (the degree to which a variable is influenced by others). The technique helps in understanding the stability and dynamism of a system by analyzing how changes in one variable may propagate through the system. In the present study, the different variables are categorised as follows:

i. **Autonomous Variables (Low Driving, Low Dependence):** These variables are reflected in Quadrant 1. These variables are relatively disconnected from the system. They neither influence nor are significantly influenced by other variables.

ii. **Dependent Variables (Low Driving, High Dependence):** These variables are reflected in Quadrant 2. These variables are greatly influenced by others but exert little influence themselves.

iii. **Linkage Variables (High Driving, High Dependence):** These variables are placed in 3rd Quadrant. These variables have strong influence and are also highly influenced. They are volatile and unstable, creating feedback loops. These variables not only effect other variables but can also be affected by them.

iv. **Driver Variables (High Driving, Low Dependence):** These variables are placed in the 4th Quadrant. These are the most influential variables that affect many others but are themselves relatively independent.

Results

As per the ISM approach outlined in methodology section, a pairwise connection "Structural Self-Interaction Matrix (SSIM)" (Table 1) is generated by a group judgment of experts. Further, based on SSIM, "Reachability Matrix (RM)"

(Table 2), “Final Reachability Matrix (FRM)” (Table 3) and Level Partition Matrix (LP) (Table 4) were generated by utilizing SmartISM program.

Table 1
Structural Self-Interaction Matrix (SSIM)

Critical Success Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
CSF1		X	V	V	V	V	V	O	V	V	V	V	V	V	V	V
CSF2			O	V	V	V	V	V	V	V	V	V	V	V	V	V
CSF3				O	V	V	V	V	V	V	V	V	V	V	V	V
CSF4					V	V	V	V	V	V	V	V	V	V	V	O
CSF5						O	X	V	V	V	O	V	V	V	V	V
CSF6							X	V	V	V	V	V	V	V	V	V
CSF7								V	V	V	V	V	O	V	V	V
CSF8									O	X	V	V	V	V	V	V
CSF9										O	V	V	V	V	V	A
CSF10											V	V	O	V	V	V
CSF11												O	X	V	V	V
CSF12													O	V	V	V
CSF13														V	V	X
CSF14															O	V
CSF15																O
CSF16																

Table 2
Reachability Matrix (RM)

Critical Success Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Driving Power
CSF1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	15
CSF2	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	15
CSF3	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	13
CSF4	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	12
CSF5	0	0	0	0	1	0	1	1	1	1	0	1	1	1	1	1	10
CSF6	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	11
CSF7	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	1	11
CSF8	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	8
CSF9	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	6
CSF10	0	0	0	0	0	0	0	1	0	1	1	1	0	1	1	1	7
CSF11	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	5
CSF12	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	4
CSF13	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	5
CSF14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	2
CSF15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
CSF16	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	3
Dependence Power	2	2	2	3	6	6	7	8	9	9	11	11	11	14	14	13	

Table 3
Final Reachability Matrix (FRM)

Critical Success Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Driving Power
CSF1	1	1	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	16
CSF2	1	1	1*	1	1	1	1	1	1	1	1	1	1	1	1	1	16
CSF3	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	13
CSF4	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1*	13
CSF5	0	0	0	0	1	1*	1	1	1	1	1*	1	1	1	1	1	12
CSF6	0	0	0	0	1*	1	1	1	1	1	1	1	1	1	1	1	12
CSF7	0	0	0	0	1	1	1	1	1	1	1	1	1*	1	1	1	12
CSF8	0	0	0	0	0	0	0	1	1*	1	1	1	1	1	1	1	9
CSF9	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1*	7
CSF10	0	0	0	0	0	0	0	1	1*	1	1	1	1*	1	1	1	9
CSF11	0	0	0	0	0	0	0	0	1*	0	1	1*	1	1	1	1	7
CSF12	0	0	0	0	0	0	0	0	1*	0	1*	1	1*	1	1	1	7
CSF13	0	0	0	0	0	0	0	0	1*	0	1	1*	1	1	1	1	7
CSF14	0	0	0	0	0	0	0	0	1*	0	1*	1*	1*	1	1*	1	7
CSF15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
CSF16	0	0	0	0	0	0	0	0	1	0	1*	1*	1	1*	1*	1	7
Dependence Power	2	2	3	3	7	7	7	9	15	9	15	15	15	15	16	15	

Table 4
Level Partitioning (LP)

Critical Success Factors	Reachability Set R (Mi)	Antecedent Set A (Ni)	Intersection Set R(Mi) $\cap$ A (Ni)	Level
1	1, 2,	1, 2,	1, 2,	6
2	1, 2,	1, 2,	1, 2,	6
3	3,	1, 2, 3,	3,	5
4	4,	1, 2, 4,	4,	5
5	5, 6, 7,	1, 2, 3, 4, 5, 6, 7,	5, 6, 7,	4
6	5, 6, 7,	1, 2, 3, 4, 5, 6, 7,	5, 6, 7,	4
7	5, 6, 7,	1, 2, 3, 4, 5, 6, 7,	5, 6, 7,	4
8	8, 10,	1, 2, 3, 4, 5, 6, 7, 8, 10,	8, 10,	3
9	9, 11, 12, 13, 14, 16,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16,	9, 11, 12, 13, 14, 16,	2
10	8, 10,	1, 2, 3, 4, 5, 6, 7, 8, 10,	8, 10,	3
11	9, 11, 12, 13, 14, 16,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16,	9, 11, 12, 13, 14, 16,	2
12	9, 11, 12, 13, 14, 16,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16,	9, 11, 12, 13, 14, 16,	2
13	9, 11, 12, 13, 14, 16,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16,	9, 11, 12, 13, 14, 16,	2
14	9, 11, 12, 13, 14, 16,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16,	9, 11, 12, 13, 14, 16,	2
15	15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,	15,	1
16	9, 11, 12, 13, 14, 16,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16,	9, 11, 12, 13, 14, 16,	2

The ISM-derived hierarchical model (Fig. 1) reveals a clear multi-level structure of the CSFs. At the apex of the hierarchy are CSF1 and CSF2, which both have the highest driving power (16) and minimal dependence (2). In the level-partition table, CSF1 and CSF2 appear together at Level 6. This indicates that these two factors act as the root drivers of the system: virtually all other CSFs are reachable from them, while they themselves are little influenced by others. By contrast, at the opposite end of the hierarchy, CSF15 stands alone at Level 1 (bottom) with *very low driving* (3) and the highest dependence (16). In other words, CSF15 functions as an outcome or emergent effect of the system, depending strongly on virtually all upstream factors.

Between these extremes, CSFs are stratified by intermediate driving–dependence profiles. CSF3 and CSF4 occupy Level 5, each with driving power 13 and dependence 3, signifying that they are significant secondary drivers – influenced by the level 6 factors but in turn influencing many below. The next, Level 4 contains CSF5, CSF6, and CSF7 (driving = 12, dependence = 7 for each); these form an intermediate stratum that mediates between higher and lower-level factors. Level 3 includes CSF8 and CSF10 (driving 9, dependence ~ 9), marking them as bridging factors

affected by and affecting several other CSFs. Finally, Level 2 groups CSF9, CSF11, CSF12, CSF13, CSF14, and CSF16 (each with driving 7 and dependence ≥ 9). These Level 2 factors are largely dependent outcomes: they are weak drivers (influence few others) but have high dependence on the upper levels.

In summary, the ISM hierarchy suggests a cascade of influence. The topmost CSFs (at Levels 6 and 5) are foundational enablers that drive the system, whereas the bottom levels are the manifest outcomes. In the context of India's financial sector and robo-advisor adoption, this implies that underlying enablers form the base of the adoption process. These enable the mid-level mechanisms (CSF5, CSF6, CSF7, and CSF8, CSF10) which in turn generate the observable dependent factors (CSF9, CSF11, CSF12, CSF13, CSF14, CSF16) and ultimately the end-state (CSF15). The placement of a CSF high in the hierarchy (e.g. level 6 or 5) indicates it is a systemic driver whose improvement will percolate through the chain; a low-level CSF (levels 1 and level 2) is an outcome that can only change if its antecedents change.

The MICMAC analysis classifies the CSFs by their driving and dependence powers, yielding insight into their roles. In this case two independent quadrant CSFs emerge: CSF1 and CSF2 have *very high driving* (16) and *very low dependence* (2). These clearly lie in the *independent (driver)* quadrant, meaning they are fundamental drivers with little backward influence. CSF3 and CSF4, with high driving (13) and low dependence (3), similarly act as primary drivers. CSF5, CSF6, and CSF7 (each with driving 12, dependence 7) also fall in independent variable quadrant but these are borderline independent variables. At the other extreme, dependent quadrant CSFs include CSF9, CSF11, CSF12, CSF13, CSF14, CSF15, and CSF16. These all have low driving (7 or less) and very high dependence (9–16). They fall into the dependent/outcome category for example, CSF15's driving is 3 while its dependence is 16. This indicates that these CSFs cannot change the system by themselves but rather reflect the state of other factors.

CSF8 and CSF10 (driving 9, dependence 9) lie in the *linkage* region means they affect others they are also influenced by many others. Notably, no CSF falls into the autonomous (isolated) quadrant, and this shows that all factors have at least moderate influence or dependence, reflecting the tightly coupled nature of robo-advisor adoption factors.

Interpretively, the MICMAC classification reinforces the ISM structure. The independent (high drive) CSFs can be seen as levers. The dependent CSFs serve as endpoints, impacted by many others. Linkage CSFs (middle-tier factors) must be managed carefully, since changes in them both affect and are affected by the system. In the Indian robo-advisory context, this suggests policymakers and firms should prioritize the identified independent CSFs (e.g. those at Level 5–6) to catalyze progress, while recognizing that the dependent CSFs will improve only once those deep drivers are addressed.

Discussion & Conclusion

This study aimed to identify and structurally analyze the critical success factors (CSFs) influencing the adoption of Robo-Advisors in emerging markets, with a specific focus on the Indian context. By employing Interpretive Structural Modeling (ISM) and MICMAC analysis, we provide a systemic understanding of the interdependencies among the identified CSFs advancing the existing literature on digital financial services adoption and responding to the limitations of purely correlational or regression-based models. The findings are discussed with reference to the study's three research questions.

The analysis uncovered sixteen CSFs, encompassing technological, institutional, cognitive, and behavioural dimensions. These include Technological Infrastructure [CSF1], Investment Performance [CSF2], Perceived

Usefulness [CSF3], Data Privacy Compliance [CSF4], Low Cost [CSF5], Customer Relationship Management [CSF6], Customer Financial Literacy [CSF7], Local Language Support [CSF8], Perceived Trust [CSF9], Hybrid Human Support [CSF10], Transparent Communication [CSF11], Financial Inclusion [CSF12], Efficient Rebalancing [CSF13], Reliable Customer Service [CSF14], Willingness to Adopt [CSF15], and Awareness and Understanding [CSF16]. The findings reported in this study align closely with extant empirical work grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), particularly with respect to the constructs of performance expectancy (CSF2, CSF3), effort expectancy (CSF1, CSF6), trust (CSF9), and facilitating conditions (CSF7, CSF8, CSF16). Notably, the present investigation extends such models by integrating contextually salient enablers—namely Local Language Support (CSF8) and Hybrid Human Support (CSF10). These variables capture elements that are especially pertinent in the Indian fintech sector, where limited digital literacy and pronounced cultural heterogeneity persist as key impediments to technology diffusion (Manaf et al., 2024; Hassan et al., 2023). Collectively, these findings favour the belief that adoption behaviour within emerging markets is not only influenced by the personal perceptions but a complex set of systemic and socio-technical factors.

ISM framework is characterized by a six level hierarchy in which the 12 strategic components are ranked in their driving and dependence capacities. The bottom level Level 6 includes Technological Infrastructure and Investment Performance which has the greatest driving force and least dependence within the model. These factors act as enablers on the bottom-level of the adoption ecosystem and are the enabling conditions that allow all other variables to be able to work. Their function thus parallels that of “facilitating conditions” in UTAUT (Venkatesh et al., 2003) and corroborates empirical findings in Milani (2019) and Belanche et al. (2019), wherein platform quality and expected returns were shown to exert a pronounced influence on adoption intentions. The fourth layer of the adoption framework is CSF5 to CSF7 which are Perceived Usefulness, Data Privacy Compliance, Low Cost, Customer Relationship Management and Customer Financial Literacy which are in the middle of structural prerequisites and service-specific characteristics. The former, Perceived Usefulness (CSF3), and the latter, Data Privacy Compliance (CSF4), each underscore the individualized evaluations and institutional obligations that shape user intent. Low Cost (CSF5), Customer Relationship Management (CSF6), and Customer Financial Literacy (CSF7) occupy a second, overlapping role, mediating between users, service providers, and the external environment. Such a dual role makes them both influencers and intermediaries and, thus, demonstrates the iterative process according to which service design, pricing strategies, and educational initiatives support each other. The third tier is occupied by CSF8 to CSF10, which are Local Language Support, Technical Support, and Hybrid Human Support, and they are operational contingencies. They address behavioural frictions frequently encountered in digitally underserved populations (Manaf et al. 2024) by accommodating local language needs and hybrid interaction preferences.

The upper tiers Levels 2 and Level 1 are populated by outcome centric CSFs, including Perceived Trust [CSF9], Transparent Communication [CSF11], Financial Inclusion [CSF12], Efficient Rebalancing [CSF13], Reliable Customer Service [CSF14], Awareness and Understanding [CSF16], and ultimately, Willingness to Adopt [CSF15], which occupies the apex. This investigation scrutinizes the interplay among contextual factors—designated here as critical success factors (CSFs)—to elucidate their hierarchical role. The low dependence powers and strong driving capacities are signs that these aspects are the results of interaction contexts but not independent, causal determinants. A regular use of MICMAC analysis provides four quadrants divided by driving and dependence characteristics. Among the most influential independent drivers stand Technological Infrastructure [CSF1] and Investment Performance [CSF2], both characterised by high driving power and low dependence. These variables are therefore essential in the activation of the system and they should be prioritised in the strategic planning. Perceived Usefulness [CSF3], Data Privacy Compliance [CSF4], Low Cost [CSF5], Customer Relationship Management [CSF6], and Customer Financial Literacy [CSF7] likewise occupy the driver quadrant, functioning as instrumental enablers.

Linkage factors characterised by concurrently high driving and dependence power constitute Local Language Support [CSF8] and Hybrid Human Support [CSF10]. These critical success factors act as sensors to both upstream and downstream variations of the e-commerce system. To this effect, they require dynamic monitoring. Systems-theoretically, they spread systemic changes at the same time as being susceptible to disturbances. Therefore, the interventional efforts in these areas can have a significant impact, but their systemic interrelatedness requires carefulness.

The dependent quadrant is comprised of Perceived Trust [CSF9], Transparent Communication [CSF11], Financial Inclusion [CSF12], Efficient Rebalancing [CSF13], Reliable Customer Service [CSF14], Awareness and Understanding [CSF16], and Willingness to Adopt [CSF15]. These elements are outcome measures, which capture the cumulative impacts of structural and behavioural enabling conditions. Contrary to several TAM-based studies that treat trust as an antecedent (e.g., Belanche et al., 2019), the present model situates Perceived Trust [CSF9] as a dependent variable, shaped by upstream capabilities such as platform reliability, cost transparency, and customer literacy. The empirical results showed that none of the elements of the cloud-based services framework were located in the autonomous quadrant, which in turn signified a very interdependent system. This observation corroborates the theoretical conclusions of Hassan et al. (2023), who assert that digital finance ecosystems in emerging markets are defined by tightly coupled enablers and outcomes.

7. IMPLICATIONS AND CONTRIBUTIONS

Theoretically, this study contributes to the fintech adoption literature by moving beyond variable-centric models to a structurally grounded, systems-oriented understanding of how adoption enablers operate hierarchically. By integrating ISM and MICMAC methods, the research not only identifies key CSFs but clarifies their relational positioning and cumulative influence. This modelling approach addresses a critical gap in existing research, which often fails to account for the directional flow and feedback among CSFs.

Practically, the findings offer actionable insights for fintech firms, regulators, and policy actors. For fintech firms, investment in Technological Infrastructure [CSF1], Investment Performance [CSF2], and Data Privacy Compliance [CSF4] should be prioritized, as these exert the strongest systemic influence. Simultaneously, demand-side interventions aimed at improving Customer Financial Literacy [CSF7] and Awareness and Understanding [CSF16] can accelerate user readiness and trust-building. Localized features such as Local Language Support [CSF8] and Hybrid Human Support [CSF10] are particularly pertinent in India's diverse linguistic and cultural landscape.

For policymakers, the model advocates for the enhancement of digital infrastructure and regulatory frameworks that protect user data and enable performance accountability. Initiatives such as digital literacy programs, vernacular access tools, and incentivized low-cost models could significantly uplift the ecosystem's readiness for Robo-Advisory services.

References

1. Abhijith R, Bijulal D (2020) *Artificial Intelligence in Fintech: Behavioural Factors Influencing Robo-Advisor Adoption*
2. Acquisti A, Taylor C, Wagman L (2016) The economics of privacy. *J Econ Lit* 54(2):442–492
3. Arenas-Parra M, Rico-Pérez H, Quiroga-Garcia R (2024) The emerging field of Robo Advisor: A relational analysis. *Heliyon*, 10(16)

4. Belanche D, Casaló LV, Flavián C (2019) Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Manage Data Syst* 119(7):1411–1430
5. Buckley RP, Arner DW, Zetsche DA (2023) Evolution of FinTech. *FinTech*, 11–26. <https://doi.org/10.1017/9781009086943.003>
6. Buttle F, Maklan S (2019) Customer relationship management: concepts and technologies. Routledge
7. D’Acunto F, Prabhala N, Rossi AG (2019) The Promises and Pitfalls of Robo-Advising. *Rev Financial Stud* 32(5):1983–2020. <https://doi.org/10.1093/rfs/hhz014>
8. Dellaert BGC, Baker T, Johnson EJ (2024) Regulating robo-advice for consumers’ financial decisions: The interplay between algorithm quality & digital choice architecture. *Behav Sci Policy*, 23794607241296690
9. Demircuc-Kunt A, Klapper L, Singer D, Ansar S, Hess J (2018) The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. World Bank
10. D’Hondt C, De Winne R, Ghysels E, Raymond S (2020) Artificial intelligence alter egos: Who might benefit from robo-investing? *J Empir Finance* 59:278–299
11. Eppler MJ, Wittig D (2000) Conceptualizing Information Quality: A Review of Information Quality Frameworks from the Last Ten Years. *IQ* 20(0):0
12. Frost J, Gambacorta L, Huang Y, Shin HS, Zbinden P (2019) BigTech and the changing structure of financial intermediation. *Economic Policy* 34(100):761–799
13. Gomber P, Kauffman RJ, Parker C, Weber BW (2018) On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *J Manage Inform Syst* 35(1):220–265
14. Gomber P, Koch J-A, Siering M (2017) Digital Finance and FinTech: current research and future research directions. *J Bus Econ* 87:537–580
15. Huang MH, Rust RT (2021) A strategic framework for artificial intelligence in marketing. *J Acad Mark Sci* 49(1):30–50. <https://doi.org/10.1007/s11747-020-00749-9>
16. Jagtiani J, Lemieux C (2017) Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information Federal Reserve Bank of Philadelphia. In *Research Department, Federal Reserve Bank of Philadelphia* (Issue 1)
17. Kandpal V, Mehrotra R (2019) *FINANCIAL INCLUSION: THE ROLE OF FINTECH AND DIGITAL FINANCIAL SERVICES IN INDIA*
18. Koenig-Lewis N, Palmer A, Moll A (2010) Predicting young consumers’ take up of mobile banking services. *Int J Bank Mark* 28(5):410–432
19. Lee I, Shin YJ (2018) Fintech: Ecosystem, business models, investment decisions, and challenges. *Bus Horiz* 61(1):35–46
20. Liu C, Yang M, Wen M (2023) Judge me on my losers: Do robo-advisors outperform human investors during the COVID-19 financial market crash? *Prod Oper Manage* 32(10):3174–3192
21. Lusardi A, Mitchell OS (2014) The economic importance of financial literacy: Theory and evidence. *Am Economic Journal: J Economic Literature* 52(1):5–44
22. Mahmud K, Joarder MMA, Muheymin-Us-Sakib K (2022) Adoption factors of FinTech: evidence from an emerging economy country-wide representative sample. *Int J Financial Stud* 11(1):9
23. McKelvey B, Kaminska R, Salmador MP, Escoffier N (2021) Management in the age of digital business complexity. Routledge
24. Milne GR, Culnan MJ (2004) Strategies for reducing online privacy risks: Why consumers read (or don’t read) online privacy notices. *J Interact Mark* 18(3):15–29

25. Nourallah M, Öhman P, Walther T, Nguyen DK (2025) Financial Robo-Advisors: A Comprehensive Review and Future Directions. *Available at SSRN*
26. Óskarsdóttir M, Bravo C, Sarraute C, Vanthienen J, Baesens B (2019) The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analytics. *Appl Soft Comput* 74:26–39
27. Ozili PK (2018) Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Rev* 18(4):329–340
28. Parasuraman A (2000) Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *J Service Res* 2(4):307–320
29. Rawlins B (2008) Measuring the relationship between organizational transparency and employee trust. *Public Relations Journal*, 2
30. RBI (2021) Report of the Working Group on Digital Lending including Lending through Online Platforms and Mobile Apps. Reserve Bank India, 151
31. Rogers EM (2003) *Diffusion of innovations* (Simon and Schuster, Ed.; 5TH ed.)
32. Romanosky S, Telang R, Acquisti A (2011) Do data breach disclosure laws reduce identity theft? *J Policy Anal Manag* 30(2):256–286
33. Sahay R, Allmen U, Lahreche A, Khera P, Ogawa S, Beaton K (2020) The Promise of Fintech Financial Inclusion in the Post COVID-19 Era. *Departmental Papers, 2020*. <https://doi.org/10.5089/9781513512242.087>
34. Sironi P (2016) FinTech innovation: from robo-advisors to goal based investing and gamification. Wiley
35. Size DIM (2023) share & growth report, 2030. *Market Research Reports & Consulting/Grand View Research, Inc.* URL: <https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-aimarket> (Дата Звернення: 23.05. 2024)
36. Suri T, Jack W (2016) The long-run poverty and gender impacts of mobile money. *Science* 354(6317):1288–1292
37. Suryono RR, Budi I, Purwandari B (2020) Challenges and trends of financial technology (Fintech): a systematic literature review. *Information* 11(12):590
38. Vallarino D (2024) Dynamic portfolio rebalancing: A hybrid new model using gnns and pathfinding for cost efficiency. *ArXiv Preprint ArXiv:2410.01864*
39. Van Rooij M, Lusardi A, Alessie R (2011) Financial literacy and stock market participation. *J Financ Econ* 101(2):449–472
40. Venkatesh V, Thong JyL, Xu X Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology by Viswanath Venkatesh, James YL, Thong SSRN (2012) *MIS Quarterly*, 36(1), 157–178
41. Verhoef PC, Reinartz WJ, Krafft M (2010) Customer engagement as a new perspective in customer management. *J Service Res* 13(3):247–252
42. Wang H, Yu S (2021) Robo-advising: Enhancing investment with inverse optimization and deep reinforcement learning. *2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 365–372
43. Xiao JJ, Chen C, Chen F (2014) Consumer financial capability and financial satisfaction. *Soc Indic Res* 118:415–432
44. Yang Z, Fang X (2004) Online service quality dimensions and their relationships with satisfaction: A content analysis of customer reviews of securities brokerage services. *Int J Serv Ind Manag* 15(3):302–326

45. Zarsky T (2016) The trouble with algorithmic decisions: An analytic road map to examine efficiency and fairness in automated and opaque decision making. Sci Technol Hum Values 41(1):118–132

Figures

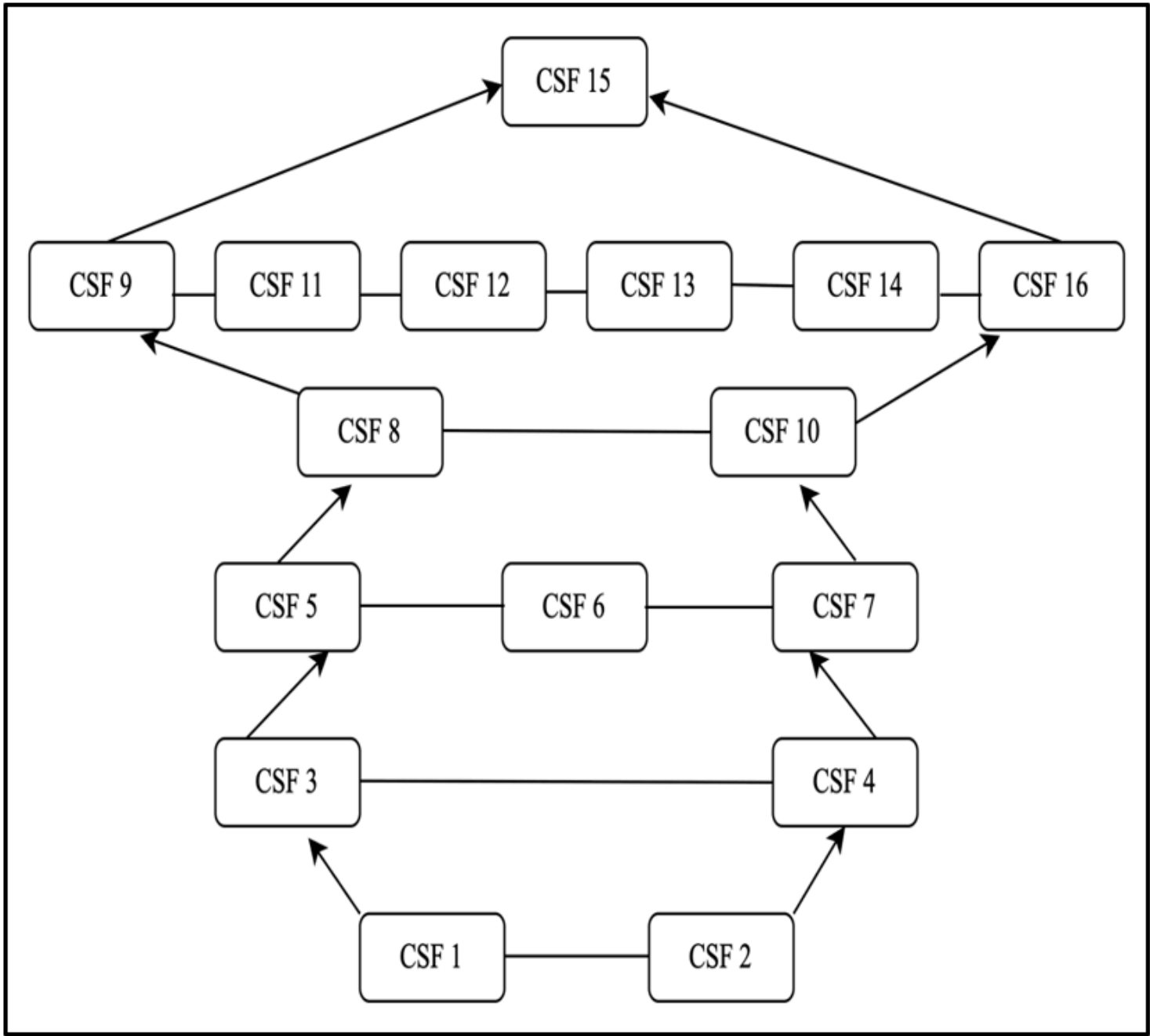


Figure 1

Level Based Hierarchical Structural Model

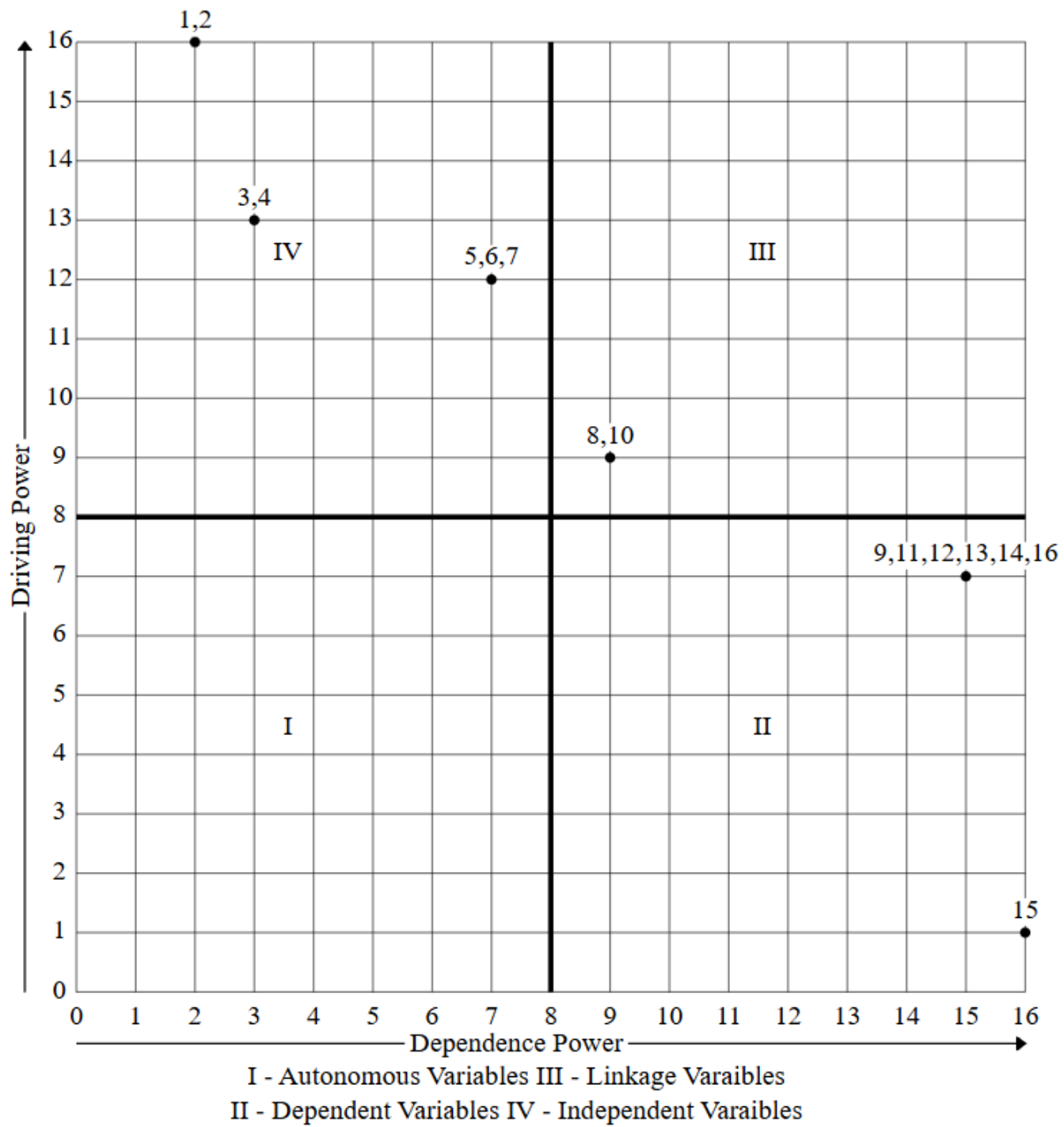


Figure 2

MICMAC Graph