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Artificial Intelligence Adoption and Corporate Financial Decision-Making: Examining the Influence of Digital Maturity on Investment, Budgeting, Risk Management, and Strategic Planning in Indian Companies

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Abstract - Artificial Intelligence (AI), covering areas like machine learning, natural-language processing, predictive analytics, and increasingly agentic decision-support systems, is gradually becoming an integral part of the finance function of Indian corporations, going far beyond back-office automation to become an integral part of the decision-making process involved in investment analysis, budgeting and forecasting, risk management, and financial planning, to name a few. The proposed paper will develop a conceptual framework and a survey-based model, testing the impact of AI Adoption (AIA) on the Quality of Corporate Financial Decision-Making (FDMQ) among Indian companies. Building on theories from the Resource-Based View, Dynamic Capabilities, and Technology-Organization-Environment models, the proposed research will suggest that the mediating role in the relationship between AIA and FDMQ is played by AI-Enabled Analytics Capability (AEAC), while the moderating role in this relationship belongs to the firm's Digital Maturity (DM). The novelty of this research project compared to the existing literature lies in its intention to collect primary data, using the structured questionnaire to survey the CFOs, controllers, FP&A managers, risk managers, and financial analysts at Indian corporations, suggesting 250-400 survey respondents. In this research paper, an outline of the development and validation process of the four scales - AI Adoption, Analytics Capability, Digital Maturity, and Financial Decision Making Quality, and formulation of five hypotheses have been done along with a nine-step analysis plan using PLS-SEM methodology for the purpose of testing mediated and moderated mediation.

***Keywords*:** Artificial Intelligence, financial decision making, AI-driven analytics capability, digital maturity, investment decisions, budgeting, risk management, financial planning, Indian firms.

1. INTRODUCTION

1.1 Background

AI has evolved from a marginal analytics application to becoming a primary input for businesses in their planning and investing activities and risk management. Machine learning-powered forecasting, natural language generation of variance explanations, anomalies detection, and increasingly more autonomous and agentic decision-making tools powered by AI are now increasingly applied in finance functions' budgeting processes, project evaluations, and risk management operations, where AI has been redefined as a strategic oversight facilitator.

There is industry evidence that suggests rapid growth in AI adoption by finance departments over the last several years as a result of the development of such tools as generative and agentic AI and increased application of AI-powered scenario modelling, predictions, and automatic variance analyses in real-time decision-making processes.

While this is taking place, however, another emerging literature identifies how the use of AI affects risk-taking behavior and resilience at the firm level: companies which possess a higher level of ability in relation to AI have been demonstrated to be able to restore their value in the face of disruptions more swiftly, handle financial restrictions better, and, in some cases, take on significantly greater risk in their investment and financial decisions based on the ability of AI to make accurate predictions. This indicates that the impact of AI on financial decision-making is not restricted merely to efficiency and costs; rather, it may well affect the decision process itself – an effect that has received less empirical examination than firm performance or stock market results.

1.2 The Indian Context

The country of India stands out as a pertinent case study of this question due to the relatively limited literature on the topic in this country. Reports produced in partnership by international consulting firms and industrial associations note that the majority of companies in India are either partially ready for the

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implementation of AI technologies into their activities or are already quite prepared to introduce AI technologies and further plan to use AI in a rapid manner, with the financial services industry, together with manufacturing and healthcare, often noted as the areas where the impact of AI will be especially significant.

At the same time, studies conducted at the national and comparative levels prove that AI adoption and digital maturity are mutually reinforcing concepts and are not independent; the more digitally mature the company, the higher chances that it will be able to adopt AI successfully and vice versa. It means that the advantage gained by a certain Indian company by adopting AI technology in finance will not be the same across different organizations and will be conditional on their digital maturity.

This unequal distribution is what makes India an interesting environment for the current study. In case the impact of AI adoption on decision making was consistent among firms, then the correct approach would just be to fast track AI adoption. On the other hand, where there is an effect from AI adoption that depends on digital readiness and how much the AI adoption has been converted into analytics within the organization, then the actions have to be more targeted – aimed at developing complementary skills that make AI adoption lead to improved budget and investment decisions.

1.3 Problem Statement and Research Gap

There are at least five major limitations common to the current body of literature in the field of the application of AI for the analysis of the interplay between corporate finance, ESG, FinTech, and behavioral finance. First, the sample of the existing body of research is dominated by the studies conducted in developed countries with little focus on the situation in India. Second, many of the studies analyze the effect of AI implementation on either financial performance or stock market returns and neglect the effect of quality of the financial decision-making process per se. Third, there are very few papers which investigate the effects of AI implementation on financial decision-making as a combination of investment decision making, budgeting, risk management, and strategic planning. These areas have been researched separately. Fourth, little attention has been paid to the effects of organization characteristics such as size, level of digitization, and governance on the impact of AI implementation on decision-making. Fifth, in terms of methodology, the majority of the studies use secondary data based on disclosures or surveys, while only a few of them use primary data collected from finance professionals.

Collectively, previous studies have focused on the association between artificial intelligence and financial performance of firms or their market results. On the other hand, relatively few studies have explored the impact of AI on financial decision making in Indian firms and the effect of organization-related factors like firm size on such associations has yet to be explored.

1.4 Research Objectives

The current research endeavors to fill these gaps by developing (i) an original survey tool for measuring AI Adoption in finance through the finance professionals themselves, without resorting to the existing proxy based on secondary information about disclosure, and (ii) the moderated-mediation model where AI-Enabled Analytics Capability is suggested as the mechanism through which AI Adoption impacts the quality of Financial Decision-Making, and Digital Maturity is seen as the moderator of this impact due to higher absorptive capacity of digitally mature firms in transforming AI tools into insights useful for making decisions. Namely, the purpose of this study is to (i) construct and validate the AI Adoption scale covering investments, budgeting, risk management, and strategic planning; (ii) investigate the direct impact of AI Adoption on the perceived quality of financial decision-making of corporations operating in India; (iii) assess AI-Enabled Analytics Capability as a mediator of this relationship; (iv) assess Digital Maturity as a moderator; and (v) provide the statistical analysis methodology to be applied to the questionnaire data collected from finance professionals.

1.5 Significance and Scope of the Study

Scope of the research includes Indian companies - listed firms and big private companies from manufacturing, financial services, IT/ITES, FMCG and other sectors, where the finance function has started using AI tools for at least one of four decision areas - investment analysis, budgeting/FP&A, risk management, or strategic financial planning. The target audience is finance professionals with positions such as CFO, finance controller, FP&A manager, treasury/risk manager, or financial analyst. Three points make this research significant. First, it adds to the body of knowledge on the subject of AI adoption and financial decision-making, testing the framework in the Indian environment, where most existing evidence is either descriptive or based on developed-markets or China firm-level data. Second, methodologically, it develops and provides a survey tool to collect primary data that can be replicated to measure professional judgment on the quality of decision-making, thus helping address the identified lack of primary evidence from finance professionals. Third, practical significance of the study is providing CFOs, boards, and policy-makers with an empirically-testable framework to determine when and under what organizational conditions it is worth investing in AI technology in the finance function to make better decisions and not only faster ones.

1.6 Structure of the Paper

The rest of the paper is structured as follows. In section 2, the existing theoretical and empirical studies concerning the usage of AI, analytical ability, digital maturity, and decision-making process in finance will be reviewed, and the theoretical foundation of the model under investigation will be developed. Section 3 is devoted to the research methodology and hypotheses formulation. Section 4 covers the research design, which includes information about the population and the sample, questionnaire development, measurement of the constructs, and nine-step statistical analysis procedure. Section 5 considers theoretical, methodological, and practical implications of the research. Limitations of the proposed design and future research directions are discussed in section 6.

2. LITERATURE REVIEW

2.1 Theoretical Foundations

Three mutually reinforcing theoretical frameworks underpin the research. Firstly, the Resource-Based View (RBV) states that sustainable competitive advantage stems from the firm's possession of valuable, rare, inimitable, and non-substitutable resources. The AI algorithms, custom-built data pipelines, and specific skills needed to apply them become just such a resource, hard to copy by competitors due to its reliance on unique firm's data, processes, and culture (Barney, 1991). From the RBV standpoint, the impact of AI adoption will depend on its embedding as an organizational competence rather than use as a separate tool.

Secondly, Dynamic Capabilities Theory expands the concept by saying that the firm not only needs valuable resources but also needs to be able to sense opportunities, invest into them, and transform itself accordingly to benefit from the technological change (Teece, 2007). Such framework explains why AI-Enabled Analytics Capability is being modeled as a mediator in this research. The existence of AI tools alone within the finance department won't lead to better decision-making, because the organization must possess a certain complementary competence to translate AI outputs into valuable insights.

Thirdly, the Technology-Organization-Environment (TOE) model, along with digital maturity, contributes to an understanding of the reason behind the systematic variation of the influence of adopting AI on decision-making outcomes among organizations. A recent study incorporates the adoption models like the TOE model along with the construct of digital maturity based on dynamic capabilities theory, revealing that the capability of an organization in progressing from the adoption of AI to its institutionalization and process embedding is contingent on organizational readiness rather than adoption only (Dey & Ghose, 2025). Fourth, another perspective to be considered is behavioral decision theory. The adoption of AI may contribute to the improvement in the quality of decisions due to the bounded rationality of managers who make financial decisions using heuristics and partial information (Simon, 1955). However, firm financial performance is also influenced by the market and macroeconomic environment.

2.2 AI Adoption and the Quality of Financial Decision-Making

The literature that applies to practice and industry highlights the correlation between the use of AI technology in finance and better quality decisions. The use of AI technology is said to enable finance professionals to perform real-time analysis of financial streams, detect risks, and plan using predictive intelligence, which changes the role of finance departments from being report-oriented to forward-looking. In the area of FP&A, the use of AI enables detection of anomalies and variances to help finance departments detect any deviations from expected patterns faster than through manual analysis, and the ability to model various scenarios before investing in any of them.

At the level of decision-making domain of the individuals, there are numerous uses of AI application in budgeting, investment appraisal, and risk management. In budgeting and forecasting, AI tools are used to manage budgets dynamically depending on real-time performance, for explaining variances between actual results and budgeted figures, and improving forecast accuracy by using real-time and historical data. In risk management, risk management applications that use AI techniques are employed to detect possible risks in markets,

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credits, and operations; and also develop early warning systems which will detect deviations from plans of performance. In the area of investment and capital allocation decisions, it is found that AI adoption leads to significantly increased risk taking attitude of firms in their investment and finance decisions, because AI's predictive capability makes managers bold (Chen et al., 2024, as cited in the literature of financial distress forecasting). Supporting evidence reveals that AI adoption increases firms' resiliency to risks and also improves their risk management capability by increasing total factor productivity, and easing the finance constraint through resource effects, and also enhances talent acquisition efforts of firms (Liu et al., 2025, as cited in the literature of financial distress forecasting).

2.3 The Mediating Role of AI-Enabled Analytics Capability

As per the dynamic capabilities theory, various recent studies suggest that the impact of AI adoption on organizational outcomes does not occur directly but is mediated by some intervening organizational capability. In a study on the impact of AI adoption on organizational performance using a sample of managers from medium-size enterprises, it was found that the positive perceptions about AI impacts on organizational performance both directly and indirectly via organizational agility, implying that a firm-level capability variable accounts for most of the impact of AI adoption on the outcomes (where organizational agility acts in the same way as the analytics-capability variable suggested in this research). Similar is the case of AI-enabled digital transformation in industrial firms where green digital innovation mediates the impact of AI-based transformation on firm performance.

In application to finance, this means that the adoption of AI in the finance function will not enhance the quality of decision making directly and universally; instead, it should affect decision making via the organization’s AI-Enabled Analytical Capability, meaning the capability of integrating AI techniques in finance processes, having reliable source data for AI, and developing analytical expertise necessary to use the output generated by AI. It echoes an established observation in the literature on information systems that the value of IT is delivered via intermediate capability-building processes, not via technology itself.

2.4 The Moderating Role of Digital Maturity

The concept of digital maturity is a recurring boundary condition in the literature on AI adoption. The phenomenon of digital maturity has been viewed as a necessary condition as well as an outcome of successful AI adoption; that is, companies with higher digital maturity levels will be more likely to experience successful AI adoption, and AI adoption will, in turn, increase their digital maturity level through better processes and organizational learning (OECD, 2025). In manufacturing environments, the phenomenon of AI maturity, which implies the institutionalization of AI usage within the company’s operations rather than technological readiness of the firm in general, has proven to influence the effectiveness of generative AI adoption strategies in terms of organizational performance improvement.

Research in the industry sector also reveals that companies with mature AI adoption have a broader presence on the cloud, advanced data technologies, and connections, and experience greater success in terms of profits from their investments in AI and generative AI programs than companies that do not have mature AI adoption, along with the higher likelihood of measuring outcomes rather than just adoption (Deloitte, 2026). Based on the literature reviewed above, it is reasonable to consider Digital Maturity as a moderating variable instead of a control one, meaning that companies with high levels of digital maturity will make higher quality financial decisions based on AI adoption.

2.5 AI Across Investment, Budgeting, Risk Management, and Strategic Planning

An alternative body of literature investigates the impact of AI at the level of individual finance functions as opposed to aggregate firm-level impacts. In FP&A, it is noted that AI technologies progress from being supportive to enabling strategic planning and improved risk management through the use of natural language generation in converting large sets of data into a story-telling mechanism for communicating insights to business executives and other stakeholders. The role of AI in strategic financial planning consists in supporting the ability of finance executives to make proactive data-driven strategic decisions using scenario modeling and decision intelligence tools and in predicting the effect of different factors on the future performance through predictive analytics. Similar reports about the application of AI by Indian financial institutions highlight the shift from intuition-based decision-making towards data-driven decision-making augmented by the use of AI in the Indian financial environment due to the widespread plans among Indian financial organizations to implement generative AI applications.

2.6 The Indian Context and Research Gap

Although the Indian evidence base is growing rapidly, it is still primarily descriptive: studies of adoption intentions and organizational readiness have been carried out by industry and consultancy reports; there have been some studies at the firm level that analyze the impact of AI on its structure and efficiency in India in relation to startups, yet there is a lack of evidence based on primary data regarding the impact of AI adoption on the quality of financial decisions of Indian organizations – investments, budgeting, risk management, and strategic planning in combination. It is exactly this gap that the current study seeks to fill.

Table-1: Summary of Key Reviewed Studies

Study	Context / Sample	Key Finding Relevant to This Study
Ganuthula & Kuruva (2025)	914 Indian knowledge-intensive start-ups	AI adoption reshapes firm structure and efficiency; effects are not uniformly positive, motivating capability-based mediation.
Dey & Ghose (2025)	Qualitative-descriptive, secondary case data	Combines TOE and dynamic capabilities theory with digital maturity to explain progression from AI adoption to institutionalized use.
OECD (2025)	Cross-country SME survey	Digital maturity and AI adoption are mutually reinforcing; digital maturity is both a prerequisite and consequence of AI adoption.
Deloitte (2026)	Global digital transformation survey (2023-2025)	Mature AI adopters report higher ROI from AI and broader complementary technology investment.
Protiviti & CII (2025)	Indian enterprise survey	Majority of Indian enterprises moderately/fully prepared to integrate AI; AI seen as a strategic decision-making priority.
Maheshwari (2025)	Indian financial sector, mixed-method	AI shifts Indian financial decision-making from intuition-based to data-driven, AI-augmented methods.
Liu et al. (2025) / Chen et al. (2024)	Firm-level financial distress studies	AI adoption strengthens risk management and resilience but may also raise risk propensity in investment/financing decisions.
AI maturity in manufacturing study (2026)	Manufacturing firms, GenAI adoption	AI maturity (distinct from general digital transformation) shapes how adoption translates into performance gains.
Barney (1991); Teece (2007)	Foundational theory	RBV and Dynamic Capabilities Theory justify treating AI-enabled analytics as a capability, not merely a resource.

Summary and synthesis of this review highlight three reasons for conducting the present study. Firstly, there is no doubt that there is strong literature to show that AI adoption leads to better risk management, better forecasting ability, and better planning ability, but the same has not been found in empirical research where the data has been collected directly from Indian financial professionals. Secondly, the analytics capability of the organizations due to AI has been strongly supported theoretically, especially on the basis of dynamic capability theory and previous mediation research on organizational agility and digital innovation, but has not been tested for its effect on financial decision-making ability of Indian organizations. Thirdly, digital maturity has been well established as a moderator condition for AI adoption results, but has not been tested for the same in the Indian context.

3. RESEARCH FRAMEWORK AND HYPOTHESES

asked on Resource Based View, Dynamic Capabilities Theory, and Technology-Organizations-Environment theory, this research presents the moderated-mediation model where AI Adoption (AIA) affects Financial Decision-Making Quality (FDMQ) directly and indirectly through AI-Enabled Analytics Capability (AEAC), with the moderating effect of Digital Maturity (DM). Financial Decision-Making Quality is defined as a multidimensional concept that consists of four sub-concepts: quality of investment decisions, budgeting and forecasting quality, risk management efficacy, and quality of strategic financial planning.

3.1 Hypothesis Development

H1: AI Adoption has a positive effect on Financial Decision-Making Quality. Finance professionals in firms with more extensive AI adoption across investment, budgeting, risk management, and strategic planning are expected to report higher perceived decision-making quality than those in firms with limited AI adoption, consistent with evidence that AI-powered tools help finance professionals surface hidden risks and optimize planning with predictive intelligence.

H2: AI Adoption has a positive effect on AI-Enabled Analytics Capability. Sustained AI use in the finance function — dashboards, predictive models, natural-language reporting tools — requires and reinforces the underlying data infrastructure, analytical skills, and workflow integration that constitute analytics capability, consistent with the dynamic capabilities logic that resource deployment builds organizational capability over time.

H3: AI-Enabled Analytics Capability has a positive effect on Financial Decision-Making Quality. Building on evidence that intervening organizational capabilities such as agility and digital innovation carry much of AI's effect on firm outcomes, it is anticipated that stronger analytics capability will be positively related to decision-making quality, independent of the raw extent of AI adoption that gave rise to it.

H4: AI-Enabled Analytics Capability mediates the relationship between AI Adoption and Financial Decision-Making Quality. Combining H2 and H3, it is proposed that a significant share of AI Adoption's effect on decision-making quality is transmitted through analytics capability rather than operating as a purely direct effect, testing the dynamic-capabilities claim that technology resources must be converted into organizational capability to generate decision-relevant value.

H5: Digital Maturity positively moderates the relationship between AI Adoption and Financial Decision-Making Quality. In line with evidence that digital maturity conditions how effectively AI adoption translates into organizational performance and that mature AI adopters extract greater returns from their AI investments, it is anticipated that Indian companies with higher digital maturity will convert a given level of AI adoption into greater gains in financial decision-making quality than less digitally mature companies.

4. RESEARCH METHODOLOGY

4.1 Research Philosophy and Design

This study applies the positivist paradigm along with a deductive type of logic for deriving hypotheses from the existing theory to test in the light of the objectives specified in Section 1.4. Specifically, the hypotheses are derived from the Resource-Based View theory, Dynamic Capabilities Theory, and TOE framework and will be tested based on primary data collected from finance professionals directly, unlike the secondary data used in the literature. This paper suggests adopting the following research design – it is a cross-sectional survey design where the structured questionnaire will be applied to finance professionals in Indian firms. A cross-sectional design based on the collection of primary data from the respondents is preferable to the secondary (disclosure-based) panel design due to three reasons. First, decision-making quality and analytics capability are not observable through disclosures but have to be collected directly from the relevant professionals; second, the professional-level survey allows testing of all four decision domains (investment, budgeting, risk management, and strategic planning) at once by a single respondent; and third, it addresses the research gap related to the lack of primary data from finance professionals.

4.2 Population and Sample

Target population is finance professionals – CFOs, finance controllers, FP&A managers, treasury and risk managers and senior financial analysts working in Indian organizations (listed companies and large private companies) who have used AI-driven tools in at least one area of finance functions. Purposive sampling technique, which could be combined with snowball sampling technique within the help of professional networks and finance / industry associations, is more suitable than simple random sampling as the population of finance professionals with actual AI experience is not enumeratable from the publicly available sampling frame. A suggested number of sample size of 250-400 respondents is suggested as per the sample size needed for stable PLS-SEM estimation and sufficient statistical power to test for moderated mediation relationships, where larger sample sizes are required compared to testing simple direct relationship. Pilot study of around 30 respondents should be carried out before the actual survey for improving wording of the questionnaire items and validating face validity.

4.3 Data Collection Instrument

Data will be gathered using a structured self-administered questionnaire provided online to finance experts and containing five components: (i) respondent profile and company information (position, years of experience, sector, company size, and listing); (ii) AI Adoption (AIA) scale; (iii) AI-Enabled Analytics Capability (AEAC) scale; (iv) Digital Maturity (DM) scale; and (v) Financial Decision-Making Quality (FDMQ) scale. Items in all constructs will be answered using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) following standard practice in studies on technology adoption and organizational capabilities. Item statements will be derived from existing scales in literature on technology adoption, dynamic capabilities, and financial decision-making and not invented, hence content validity.

4.4 Construction and Scoring of Constructs

The AI Adoption scale will consist of questions pertaining to four sub-domains of AI applications: (i) AI usage in investment analysis, (ii) AI usage in budgeting/forecasting, (iii) AI usage in risk management, and (iv) AI usage in strategic financial planning, using the four-point usage-depth scale described in Table 2 below. This will enable us to differentiate between companies that have not used any specific application of AI, companies that have used it sparingly or moderately, and those that have used it extensively and with specific results.

Table-2: Variable Definitions and Data Sources

Variable	Type	Measurement	Data Source
AI Adoption (AIA)	Independent	Multi-item survey score of AI usage depth in investment, budgeting, risk management, and strategic planning (0-3 scale per sub-domain, summed/averaged)	Structured questionnaire — finance professionals
Financial Decision-Making Quality (FDMQ)	Dependent	Composite of perceived investment decision quality, budgeting/forecasting quality, risk management effectiveness, and strategic planning quality (5-point Likert)	Structured questionnaire — finance professionals
AI-Enabled Analytics Capability (AEAC)	Mediator	Multi-item score of data infrastructure, analytical skill, and workflow integration of AI in finance	Structured questionnaire — finance professionals
Digital Maturity (DM)	Moderator	Multi-item score of digital infrastructure, governance, and culture	Structured questionnaire — finance professionals

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Firm Size	**Control**	**Natural log of annual revenue/total assets, or employee-count category**	**Questionnaire (firm profile) / public filings**
Firm Age	**Control**	**Years since incorporation**	**Questionnaire (firm profile)**
Respondent Experience	**Control**	**Years of experience in the finance function**	**Questionnaire (respondent profile)**
Industry/Sector	**Control**	**Industry dummy variables**	**Questionnaire (firm profile)**

Table-2: AI Adoption — Usage-Depth Scoring Rubric (per finance sub-domain)

Score	Meaning
0	No use of AI tools in this finance sub-domain
1	Aware of / piloting AI tools, no routine use
2	Routine use of AI tools in this sub-domain
3	Extensive, embedded AI use with measurable influence on decisions in this sub-domain

4.5 Operationalization of Constructs

The dependent variable FDMQ is operationalized through a second-order reflective construct that has four first-order dimensions; investment decision-making quality (accuracy and timely appraisal of investments), budgeting and forecasting quality (accuracy, adaptability, and explanation quality for variances), risk management effectiveness (ability to identify and mitigate financial risk early), and strategic financial planning quality (conformity of financial plans to strategic objectives and scenarios). The mediator, AI-Enabled Analytics Capability (AEAC), is operationalized through the capability of an organization to incorporate AI outputs in finance processes, with sound data infrastructure and analysis capability, in keeping with the dynamic capabilities perspective which considers capability separate from resource possession. Finally, the digital maturity (DM) moderator is operationalized with multi-item measures of digital maturity such as those involving data infrastructure, digital governance, and digital culture in keeping with recently published research that integrates adoption models with digital maturity constructs (Dey & Ghose, 2025).

Control variables included to reduce omitted-variable bias are:

- Firm Size (natural log of annual revenue or total assets, or employee-count category), controlling for scale-related resource advantages;
- Firm Age, as a proxy for organizational maturity and legacy-systems constraints;
- Respondent Tenure/Experience in the finance function, controlling for individual expertise effects on perceived decision quality;
- Sector/Industry, using industry dummy variables, given documented sectoral differences in AI readiness.

4.6 Statistical Analysis Plan

The analysis to be conducted will follow nine steps. Step 1 is the data cleaning and preparation step where there will be checks for missing values, presence of straight-lining or inattentive responses, and Harman's single factor test due to the fact that all constructs are self-reports of the same respondent. In Step 2, descriptive statistics such as mean, standard deviation, skewness, and kurtosis will be computed for all constructs, while demographic details including the sector, company size, and position of the respondent will be profiled. Step 3 is concerned with determining the reliability of the constructs based on the use of Cronbach's alpha and composite reliability with a minimum value of 0.70.

Phase 5 correlates the bivariate associations of AIA, AEAC, DM, FDMQ, and controls along with a correlation matrix to generate preliminary insight on the proposed associations.

Phase 6 performs multicollinearity tests through variance inflation factor (VIF) tests with the use of a cutoff value of 5 (or 10) because of the conceptual similarity between AI Adoption and Analytics Capability constructs. Phase 7 estimates the structural model through PLS-SEM or covariance-based SEM (as robustness check), tests hypotheses H1 and H3 for direct effects, and reports path coefficients, R^2, and f^2, significance of which is tested through bootstrapping (5,000 resamples).

In Phase 8, the mediation analysis is performed to assess the indirect effect of AI adoption on financial decision-making quality through AI-enabled analytics capability via bias-corrected bootstrap confidence intervals (and not Sobel test because of its better handling of non-normally distributed indirect effects), in order to examine H2 and H4. In Phase 9, the moderation and moderated mediation analysis is carried out: an interaction term, AIA x Digital Maturity, with mean centering is entered, along with the separate variables, and simple slope plots are produced for low (mean - SD), mean, and high (mean + SD) levels of digital maturity, when interaction is significant, in line with conditional process approach (Hayes, 2013). The robustness tests include estimating the model on the subsamples based on firm size and industry. Further, the estimation of financial decision making quality is conducted on an alternative single-item measure of decision quality instead of the composite one.

Structural Model Specification

The baseline structural model is expressed as follows:

$$FDMQi = \beta 0 + \beta 1AIAi + \beta 2AEACi + \beta 3DMi + \beta 4(AIAi \times DMi) + \Sigma\, \beta k\ Controlsi + \varepsilon i$$

where subscript i denotes the responding firm/finance professional and εi denotes the residual error. A second equation, used for the mediation analysis in Phase 8, is:

$$AEACi = \gamma 0 + \gamma 1AIAi + \Sigma\, \gamma k\ Controlsi + \varepsilon i$$

4.7 Validity, Reliability, and Ethical Considerations

Validity of content in the case of the scales of AI Adoption, Analytics Capability, and Digital Maturity is achieved through the adaptation of wording of items from previously validated measures of technology adoption and dynamic capabilities and through the expert review by academics and finance professionals of the instrument before testing starts rather than item generation without regard for previously validated measures. Validity of construct of Financial Decision-Making Quality is achieved through the accepted method of decision quality analysis whereby decision-making quality is decomposed into its component dimensions such as investment decisions, budgeting, risk management, and strategic planning. Since primary data are collected from individual respondents, informed consent and respondent anonymity along with confidentiality of the data should be guaranteed.

4.8 Indicative Timeline and Resource Requirements

In order to execute the proposed design, there needs to be careful planning rather than a single data collection process. The following timeline would illustrate that three to four weeks can be spent in finalizing and piloting the questionnaire (expert review and a pilot test of 30 respondents); eight to ten weeks for data collection at a large scale (with room for reminders since professional respondents are involved); two to three weeks for data cleaning, screening, and initial descriptive analysis; and four to six weeks for validating measurement model, estimating structural model, and mediating/moderating analysis, which includes robustness tests. Therefore, it is anticipated that four to five months could be needed to complete the process on an individual level. Resource needs would include online survey software, access to networks or associations (CII, ICAI, or CFO forums) where the respondents are reachable, and statistics software capable of conducting PLS-SEM/covariance-based SEM analysis (SmartPLS, R, or AMOS).

4.9 Feasibility Note

Response rates to the solicitation of an unsolicited survey among senior-level financial professionals may be poor, and hence it is advised that the data be collected using professional associations, networks of finance alumni, or finance-related groups on LinkedIn to ensure better legitimacy of responses. In cases where complete sampling of 250-400 people is not possible within the time frame of the research study, the proposed method of analysis would still be applicable to a smaller sample of 150-200 people, although with decreased ability to find the moderating effect on the mediation relationship in H5. Pilot testing of the questionnaire with 25-30 respondents is vital prior to large-scale administration.

5. EXPECTED CONTRIBUTIONS AND IMPLICATIONS

This paper has been written as a framework/methodology paper, rather than as an empirical one, as the primary survey data has yet to be obtained from finance practitioners in India for the estimation of the suggested model. After its implementation, the research paper is expected to make contributions at the following levels.

5.1 Theoretical Contributions

First, through changing the outcome variable from the financial performance of firms to the quality of financial decision-making, the research fills a particular and recurring gap within the AI and finance literature, which has tended to be too focused on performance and stock market outcomes. Second, through the formal testing of AI-Enabled Analytics Capability as a mediator, in contrast to the idea that the adoption of AI is what determines decision quality, the research expands dynamic capabilities theory into the AI in finance context, similar to earlier findings about organizational flexibility and digital innovation as a mediator of the impact of AI technology on organizational outcomes. Third, testing Digital Maturity as a moderator, not just as a background control, formally tests whether the documented relationship between digital maturity and AI adoption outcomes applies specifically to financial decision-making quality for Indian firms.

5.2 Methodological Contributions

This research presents a well-defined usage depth rating scale on four levels for AI Adoption (Table 2), which is easily usable in finance sub-fields as well as in different respondent groups, along with an effective primary data collection tool that directly resolves the issue of the lack of primary data from finance professionals found in the research gap. This is because both the data collection tool and methodology used here can be replicated in any other study related to another country/sector/industry/profession.

5.3 Practical and Policy Implications

Establishment of mediation effect (H4) will mean that CFOs and the board should look at the implementation of AI in their finance departments from the perspective of building capabilities for decision-making in their organization rather than as procurement of tools where benefits are supposed to occur automatically. The above-listed proposed AIA, AEAC, and FDMQ measures can be utilized by CFOs to build an internal readiness dashboard in order to evaluate whether investments in AI technologies in their finance departments bring any decision-making capabilities.

Confirmation of the moderation effect (H5) will mean that medium-sized organizations in India that have low levels of digital maturity will need support in building additional organizational capabilities related to data governance, digital infrastructure, and analytics capabilities to achieve the similar effects of adopting AI in their finance departments as seen in highly digitally mature firms. The findings of such studies will allow both policymakers and industry representatives to provide some concrete firm- and profession-specific evidence in addition to macro-level reports about AI-readiness of companies.

For investors and analysts, a validated Financial Decision-Making Quality measure can be used as an additional indicator of quality governance based on the decision process.

5.4 Positioning Relative to Prior Evidence

These expected findings can even be preliminary evaluated in comparison with the existing evidence without any data collection yet. H1 is expected to confirm the Indian case as being in line with general industry and academic evidence about positive impact of AI implementation on risk assessment, forecasting, and strategic planning abilities of firms. However, in contrast to industry reports used for proving this evidence, primary professional judgments will be the basis in our research. H4 is expected to confirm the existence of an idea that intervening organizational capabilities, such as organizational agility and digital innovation, take the lion's share of AI impact on firm performance in the field of financial decision-making quality specifically. H5 is expected to confirm evidence that digital maturity moderates the benefits companies get from their investments in AI, which has been proved by the previous studies. The lack of statistical significance of H5 will also be interesting because it will show that fast-growing AI readiness initiatives in India can narrow the gap in AI benefits related to digital maturity.

6. LIMITATIONS AND FUTURE SCOPE

6.1 Limitations

There are several limitations that must be taken into account when implementing this design. First of all, as Financial Decision-Making Quality and Analytics Capability are self-reported variables, there is a certain degree of social-desirability bias and common method variance, which can be mitigated but not completely eliminated via Harman's single-factor test, mixed item ordering, and anonymity assurance procedures. The second limitation of this design is that, due to purposive and snowball sampling of finance professionals, the results obtained via statistical generalization cannot be applied to all Indian finance professionals, since there is no publicly available sample frame. Finally, the cross-sectional design provides only a snapshot of a single moment in time and cannot be used to prove a direction of causality between AI Adoption, Analytics Capability, and Financial Decision-Making Quality as compared to longitudinal or panel designs.

Another limitation of this design is the possible existence of endogeneity: companies whose finance departments were making decisions of higher quality might have decided to adopt AI technology anyway, thus causing some kind of reverse causality that cannot be ruled out by means of a single cross-sectional study.

6.2 Future Research Directions

There are some opportunities for the extension of the suggested model that may be examined. First, it is possible to enlarge the scope of investigation by including small and medium-sized enterprises of India into the sample and see whether the relationships suggested are valid for the situation when there is low digital maturity and AI adoption. Second, the longitudinal study design will allow estimating whether the AI adoption at moment t predicts financial decision-making quality at t + 1 and solve, thus, the problem of endogeneity stated above. Third, by comparing the results achieved in India with those achieved in other developing countries which experience AI adoption similarly, it is possible to identify whether the suggested moderated mediation model is specific for India or applicable for the emerging market context.

7. CONCLUSION

Artificial Intelligence is redefining the way Indian firms perform investment appraisals, budgeting, risk assessment, and financial decision-making processes; however, there is limited understanding of how the linkage between AI use and decision-making processes can be established and what organizational factors contribute to stronger linkage between AI adoption and quality financial decisions, based on primary data collected from Indian finance professionals. The paper presents a moderated-mediation model of the linkage in which Artificial Intelligence-Enabled Analytics Capability acts as mediator and Digital Maturity acts as moderator of the relationship between AI Adoption and Financial Decision-Making Quality. Based on the Resource-Based View, Dynamic Capabilities Theory, and Technology-Organization-Environment Framework and informed by recent empirical studies on AI adoption, digital maturity, and financial decision-making, the model explains how AI use in the finance function helps making better financial decisions and under what circumstances.

With the development of five testable hypotheses, validated primary-data survey instrument, and nine-phase statistical analysis strategy, the article presents replicable methodology for future primary-data studies of AI adoption and financial decision-making in emerging markets, and identifies, upfront, data-gathering and measurement issues that have to be solved prior to model estimation. In practice, the paper will provide evidence about the conditions under which the adoption of AI in corporate finance functions in India leads to decision-making value, instead of assumption thereof.

In a broader sense, the paper will contribute to a growing literature base regarding AI adoption not as a unidimensional phenomenon of positive impact, but as a resource which value depends on investments made by organizations. Given the context of rapid, yet unequal adoption of AI and digital technologies in India, research designs that will enable to differentiate between AI access and AI capability, and to understand the conditions of organization under which this transition happens, will be of practical use for CFOs making budget decisions, boards/investors assessing substance of AI-related disclosures, and policymakers developing tailored programs of digital capabilities for Indian businesses of various sizes and digital maturity.

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