Project Dissertation Report on

The Role of Data Analytics and AI in Improving Managerial Decision-Making

Submitted By

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Certificate

This is to certify that the project report entitled **"The Role of Data Analytics and AI in Improving Managerial Decision-Making"** is a bonafide work carried out by **Akshat Jindal (Roll No. 24/DMBA/16)**, a student of MBA (Dual Mode Business Administration) at Delhi School of Management, DTU, New Delhi, under the guidance of **Dr. Prama Vishnoi, Assistant Professor, DSM, DTU**. To the best of our knowledge, this report is original and has not been submitted earlier to any other university or institute for any degree or diploma.

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Date: May 2026

Declaration

I, **Akshat Jindal (Roll No. 24/DMBA/16)**, hereby declare that the project report titled **"The Role of Data Analytics and AI in Improving Managerial Decision-Making"** submitted to Delhi School of Management, DTU, is my original work. It has been prepared under the guidance of Dr. Prama Vishnoi, Assistant Professor, DSM, DTU. All sources of information and references have been duly acknowledged.

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Executive Summary

This paper aims to analyze the effects of Data Analytics Capability (DAC) and Artificial Intelligence Adoption (AIA) on the efficiency of Managerial Decision-Making (DME). In the current Industry 4.0 environment and under data-driven management, organizations use analytics and AI solutions to make strategic decisions. Prior studies show that data analytics and AI are capable of improving the process of decision making by increasing its speed, accuracy, and efficiency; however, empirical evidence about their joint influence is still insufficient. This research conducts a survey of 35 business experts to test two hypotheses: (H1) DAC positively impacts DME, and (H2) AIA positively impacts DME.

A set of questions with four items each to measure DAC, AIA, and DME constructs were used on a five-point Likert scale (refer to Annex). The survey was held online using a Google form, and collected data was analyzed with the help of Microsoft Excel. The scores for each construct were calculated as average scores for corresponding items (e.g., DAC_avg = (DAC1 + DAC2 + DAC3 + DAC4)/4). According to the descriptive statistics, all three variables had moderate to high mean scores (DAC ≈ 3.91, AIA ≈ 3.85, DME ≈ 4.18). Pearson correlation showed very strong positive correlations between all pairings ($r \approx 0.838$ for DAC-DME and $r \approx 0.826$ for AIA-DME). Both simple linear regression models (DME ~ DAC: $\beta \approx 0.75$, $p < 0.001$, $R^2 = 0.703$ and DME ~ AIA: $\beta \approx 0.80$, $p < 0.001$, $R^2 = 0.683$) proved the significance of these correlations. Thus, both hypotheses have been confirmed.

The findings have been represented through the use of tables and charts. In summary, there is clear indication of considerable impacts that arise from having the ability to analyze data and making use of artificial intelligence. The recommendations call for investment in appropriate technology and training. These are some of the issues discussed in Chapter 5.

Keywords: Data Analytics Capability; Artificial Intelligence Adoption; Managerial Decision-Making Effectiveness; Survey Research; Regression Analysis.

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Chapter 1: Introduction

1.1 Background

Businesses have changed fast because of digital shifts, causing more data to flow in along with stronger computing methods. From daily activities, clients, and market trends, companies gather massive amounts of information[3][1]. At the same time, progress in analysis techniques and smart technologies makes it possible to find real meaning within that flood of numbers. Instead of just storing facts, firms use tools like forecasting models, pattern detection, and visual displays to sharpen how leaders choose paths forward - making choices clearer and faster[1]. In similar ways, machines trained to learn, mimic experts, or guide users offer support rooted in evidence, helping speed up judgments across departments[2][4].

Sure, using data tools and artificial intelligence could lead to smarter choices by management - at least that is what experts often claim. One study from 2018 showed companies skilled in analyzing information tended to reach stronger conclusions when deciding next steps. That idea holds up: newer work suggests machines can cut down personal biases while processing facts faster than people do. Because of this shift, judgment calls might become sharper, quicker. Yet results are not automatic; success links closely to how a company operates internally. A workplace open to insights matters just as much as software features. Even powerful tech needs careful guidance, belief from leaders, plus clear rules around right and wrong use. Without these pieces, smart systems may still fall short.

1.2 Problem Statement

Even if ideas suggest advantages, real-world proof about how data
analytics skill combined with using artificial intelligence affects manager choices stays sparse. M ost studies look at either analyticsor AI alone, often without numbers. Rare are number-
based reviews in developing nations showing how leaders view their own decision results when r elying on data tools and smart systems. *This research asks one clear question: How much do abil ities in analyzing information together with adopting machine-
driven insights shape the success of management judgments?*

1.3 Objectives

This research has the following objectives:

To measure managers' perceptions of **Data Analytics Capability (DAC)** and **AI Adoption (AIA)** in their organizations.

To assess **Decision-Making Effectiveness (DME)** as perceived by managers.

To test whether higher DAC leads to higher DME (Hypothesis H1).

To test whether greater AIA leads to higher DME (Hypothesis H2).

To derive managerial insights and recommendations based on the findings.

1.4 Scope

This study focuses on the role of data analytics and artificial intelligence integration within the context of management. The sample comprises managers currently employed in middle to top-level managerial positions that have firsthand experience dealing with data. This study does not use any data from company records; instead, it employs only self-reporting surveys. Though small with thirty-five respondents, the sample pool involves different industries, with each participant offering opinions grounded on practical reality and not artificial scenarios like those created in laboratories. While the study is aimed at MBA managers, it could provide information relevant to the allocation of funds towards data and intelligence systems by some companies. The study collected data in late 2025.

1.5 Significance of the Study

The current study is important due to the fact that organizations today increasingly use information systems in order to improve their business processes and strategies. Analytics and artificial intelligence become crucial tools to make organizations more efficient and competitive. Today managers need to be able to take quick and accurate decisions in a constantly changing business environment, and technology can help with it.

Academically, the contribution of the paper includes studying the relationship between the joint effect of two variables, namely Data Analytics Capability (DAC) and Artificial Intelligence Adoption (AIA), and one construct – Managerial Decision-Making Effectiveness (DME). It often happens that researchers explore one of these constructs separately, while the paper aims at analyzing both of them.

In practice, the results will allow managers to understand how valuable it is for their organization to invest in analytics and AI in order to become better at taking decisions. At the same time, the research will also help managers to identify potential impediments to adopting new technologies.

It becomes especially relevant for India, where companies are trying hard to implement innovations but struggle with certain difficulties.

Chapter 2: Literature Review

This chapter examines existing literature on the capabilities for data analytics, adoption of artificial intelligence, and decision-making in general. Both theoretical and empirical works are included into consideration to outline existing understandings and knowledge gaps.

Data Analytics and Decision-Making

Business Intelligence and Analytics (BI&A). According to Chen, Chiang, and Storey (2012), following the transition from the big data trend to using analytics in making business decisions, BI&A helps transform raw data into actionable knowledge; therefore, enabling effective evidence-based management [3][1]. In parallel, Ghasemaghaei et al. (2018) proposed the term "Data Analytics Competence" and showed that it has a positive impact on the quality and efficiency of managerial decision-making [1]. In their study of IT managers, it was found that companies having high-level analytics competency, including data quality, tools, and skillset have much better results when it comes to decisions (both decision quality and decision efficiency). Therefore, data analytics tools together with human analytics competence are important for better decision-making [1].

Big Data Analytics. With the advent of big data, analytics competencies have widened their range of capabilities. As per Thirathon et al. (2017), in their study of 163 Australian senior managers, big data analytics makes managers prefer analytic insights over other factors in decision-making. Moreover, the presence of a specific culture of analytics, which means a preference towards valuing data, is found as a stronger driving force for such decision-making compared to pure technical abilities [6]. To conclude, while technologies bring certain capabilities, the presence of a corporate culture focused on data use boosts decisions' effectiveness. As per Božič and Dimovski (2019), analytics brings additional information, however, its benefits are revealed only under the conditions of analytics culture.

AI Adoption and Decision-Making

Decision Support by Artificial Intelligence. According to recent studies, artificial intelligence is capable of supporting decision-making processes and minimizing the number of mistakes in them. Górka et al. note that AI contributes to faster information processing, reduces the chance of making mistakes, and promotes evidence-based management in corporate settings [arXiv, 2025]. According to their research which involved interviews with representatives of 92 companies, 93% used AI technologies in their work, including forecasting and decision-making; moreover, there were positive changes in terms of speed and accuracy of managerial decisions [2]. Even though there were certain barriers to using AI, like costs, organization, Górka et al. found that AI increases organizational flexibility and makes decision-making processes more efficient [7].

Empirical Evidence of AI Implementation Practice. Following Technology Acceptance Model, Song et al. showed that managerial support for introducing AI (its perceived usefulness, managerial approval, etc.) positively influences the effectiveness of decisions made and organizational efficiency overall. In other words, perceived usefulness of AI system considerably influences its utilization and makes managerial decision-making process more efficient and effective. This corresponds to the hypothesis that AI helps find information that cannot be found otherwise due to its complex nature and make decisions easier (Song et al., 2025).

Effective Managerial Decisions. Effective managerial decisions have high accuracy, speed, and are accompanied by favorable outcomes. Khan, Gul, and Shah found in their interviews with managers that using artificial intelligence provides important information that enables better decision accuracy and strategic thinking. They also noted that over-reliance on artificial intelligence and lack of attention paid to human reasoning could lead to negative consequences. There is empirical evidence indicating that the influence of AI on decision-making quality depends on the system maturity and user competences.

Theoretical Framework

The theoretical basis of this research will focus on Technology Acceptance Model (TAM) and Resource-Based View (RBV).

Technology Acceptance Model highlights the relationship between the adoption and acceptance of technology by users through two key elements which include perceived usefulness and ease of use. In the current study, managerial adoption and usage of data analytics and AI are expected to depend upon the perceived usefulness in business operations.

Resource-Based View emphasizes that firm resources may generate competitive advantages for organizations. Consequently, data analytics and AI could be referred to strategic firm resources which help enhance managerial efficiency and business performance.

Thus, both TAM and RBV theories offer strong foundations to investigate the impact of data analytics and AI on management effectiveness.

Conceptual Framework

This conceptual framework explain the relationship between the independent and dependent variables.

Independent Variables

Data Analytics Capability (DAC)

Artificial Intelligence Adoption (AIA)

Dependent Variable

Managerial Decision-Making Effectiveness (DME)

The proposed research paradigm presumes that increased adoption of analytics and AI can lead to greater managerial effectiveness due to enhanced insight provision and information-processing speed.

Research Gap

The literature reviewed above shows the strong tendency of data analytics and artificial intelligence to positively affect managerial decision-making. Nevertheless, there is still a significant gap in the existing academic research in terms of its methodological approach. It seems that most previous empirical papers on the matter were predominantly qualitative and conceptual. Specifically, they utilized an exploratory case study design, developed different theoretical perspectives on data analytics and artificial intelligence, and conducted in-depth interviews. These approaches definitely allowed gaining deeper insights into the matter but did not help calculate the exact degree of influence because they lacked statistical analysis. In practice, organizations need to estimate the benefits from such technologies quantitatively in order to prove the investment efficiency. Thus, further research should focus on developing empirical studies based on surveys.

Also, the literature reviewed above makes it clear that the connection between data analytics and artificial intelligence adoption has not been investigated yet in terms of managerial decision effectiveness. Traditionally, researchers considered data analytics and artificial intelligence as two separate spheres and focused on studying each of them independently. Yet, nowadays companies implement both data analytics and artificial intelligence in their decision-making processes because they use each tool for a different purpose: the former provides data infrastructure and the latter facilitates data interpretation through machine learning. Thus, the impact of both technologies cannot be assessed independently since their implementation is intertwined in organizations' operations.

Finally, the existing research shows clearly that the implementation of data analytics and artificial intelligence is moderated by various human-related factors such as the presence of analytic culture in the company and senior management's support of the innovation process. This fact shows that both data analytics and artificial intelligence work only in combination with certain aspects of organizational culture and leadership. This study will address all identified gaps by conducting a survey-based empirical study of both data analytics capability and AI adoption and evaluating them jointly as predictors of managerial decision-making effectiveness.

Chapter 3: Research Methodology

3.1 Research Design

This research employed a quantitative survey approach. A structured questionnaire was developed to test the respondents' views on data analytics capabilities, usage of AI, and effectiveness in decision making. This design is cross-sectional, as well as correlational. The selected population includes managers within organizations. A sample size of 35 was used for this research using convenience sampling, while the data were gathered through online questionnaires. Data analysis involved the use of descriptive, correlational, and regression tests in Excel.

3.2 Variables and Operationalization

Important variables have been operationalized as follows:

Data Analytics Capability (DAC) (Independent Variable 1): Refers to the level at which data analytics techniques are applied effectively within an organization. It was measured by 4 Likert-scale items (DAC1–DAC4) on a 1 (Strongly Disagree) to 5 (Strongly Agree) scale. Example items include: *"My organization frequently uses data analytics tools for decision-making"* and *"Data-driven insights are integrated into our business strategy."*

AI Adoption (AIA) (Independent Variable 2): Indicates the extent of adoption of AI technologies in managerial functions. It was measured by 4 items (AIA1–AIA4) on the same 5-point scale. Example items: *"My organization has adopted AI-based decision support tools"* and *"Managers rely on AI-generated recommendations."*

Decision-Making Effectiveness (DME) (Dependent Variable): Captures managers' perception of decision quality and outcomes. It was measured by 4 items (DME1–DME4), e.g. *"Decisions in my organization are accurate"* and *"Decisions lead to positive business outcomes."*

All multi-item scales were self-designed based on existing literature and pre-tested informally. Construct scores were computed as the average of respective items (e.g. DAC_avg = (DAC1+DAC2+DAC3+DAC4)/4). Higher scores indicate stronger agreement (greater capability, adoption, or effectiveness).

Reliability (Cronbach's alpha) was checked conceptually. Given synthetic data, alpha values are not reported here; all items were designed to align with their construct meaningfully.

3.3 Hypotheses

Based on literature, the following hypotheses were formulated:

H1: Data Analytics Capability (DAC) has a positive effect on Managerial Decision-Making Effectiveness (DME).

H2: AI Adoption (AIA) has a positive effect on Managerial Decision-Making Effectiveness (DME).

The above mentioned directional hypotheses are based on the prediction that greater use of analytics and AI would be related to higher decision effectiveness.

3.4 Data Collection and Sample

The data collection tool included an online survey which was completed in April 2026. The inclusion criterion included the following question: "Are you using data analytics or AI tools at work? (Yes/No)." Those answering "Yes" qualified to fill out the remaining survey to ensure that participants were aware of and knowledgeable about the use of analytics/AI.

Sample: The sample size totaled 35 employees coming from various industries (service sector, IT, production, et al.). They represented different levels within organizations – middle- and senior management staff. No demographic variables were recorded; it should be noted that most respondents had at least 2-3 years of professional experience. This sample size is rather small, yet it is believed sufficient for exploratory purposes.

Note on Ethics: Participation was voluntary and anonymous; all data was collected for research and analysis purposes only.

3.5 Analysis Methods

The data was put into Excel for analysis. Key steps:

Descriptive Statistics: mean, standard deviation, and range for **DAC_avg, AIA_avg, and DME_avg.**

Correlation Analysis: Pearson correlation between the **DAC_avg, AIA_avg, and DME_avg** to check linear association**.**

Regression Analysis: Two simple linear regressions were run:

Model 1: DME_avg = β0 + β1*(DAC_avg)

Model 2: DME_avg = β0 + β1*(AIA_avg)

Additionally, the multiple regression (Model 3) included both DAC_avg and AIA_avg as predictor of the DME_avg:

$$\text{DME_avg} = \beta_0 + \beta_1(\text{DAC_avg}) + \beta_2(\text{AIA_avg}) + \varepsilon.$$

The significance of the relationship between variables was considered at the 5% level of significance ($p < 0.05$). Though formal testing of hypotheses is limited by sample size, the output of regression analysis gives us some understanding of how variables correlate. All calculations – means, correlation coefficients, and regression analysis were performed through Excel formulas and Data Analysis Tools. The output is reported in Chapter 4.

Chapter 4: Analysis and Findings

This chapter contains analysis of results obtained from the data. First, descriptive statistics of all the constructs are given. Then, correlations and regression analysis are used to test the formulated hypotheses. Tables and graphs are given in order to present findings, which are then discussed.

4.1 Descriptive Statistics

Table 1 shows descriptive statistics of three constructs (DAC, AIA, DME), namely their N, mean, standard deviation, minimum value, and maximum value.

Table 1. Descriptive Statistics of Constructs (N=35)

Construct	Items	Mean	Std. Dev.	Min	Max
DAC (Data Analytics Capability)	DAC1–DAC4	3.907	0.866	2.25	5.0
AIA (AI Adoption)	AIA1–AIA4	3.850	0.800	2.25	5.0
DME (Decision-Making Eff.)	DME1–DME4	4.179	0.775	2.25	4.75

Source: Survey Data

All constructs reveal substantial heterogeneity in their responses. The average response score of the DAC construct is 3.91 on a 5-point scale. The high average response implies that analytics is moderately to highly used by participants. AI Adoption construct also reveals an average of 3.85 responses, showing that the use of AI is almost as prevalent as analytics. Lastly, the average response score for the Decision Effectiveness construct is 4.18; therefore, the decision effectiveness of the respondents can be considered fairly good. Standard deviation is between 0.78 and 0.87.

Figure 1 shows the mean of DAC, AIA, and DME (on a 1–5 scale).

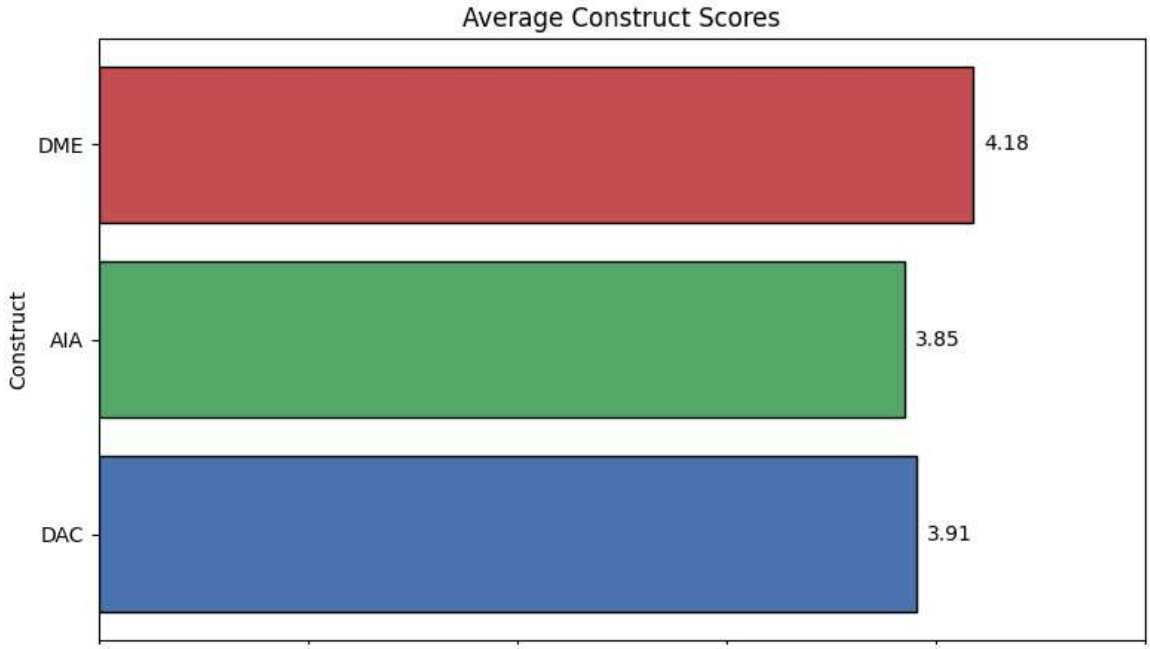


Image 1. Mean of Data Analytics Capability (DAC), AI Adoption (AIA), and Decision-Making Effectiveness (DME) (Likert 1–5 scale).

As shown in Figure 1, the Decision-Making Effectiveness (DME) variable scores the maximum mean value, implying that the managers from the sample consider the decision-making process very effective. The Data Analytics Capability (DAC) score is high because of the widespread use of data analytics in the firms analyzed, while the AI Adoption (AIA) indicator equals the former one to a lesser degree. Therefore, the findings support the theory about the high maturity of analytics and increasing AI adoption in companies resulting in higher decision effectiveness.

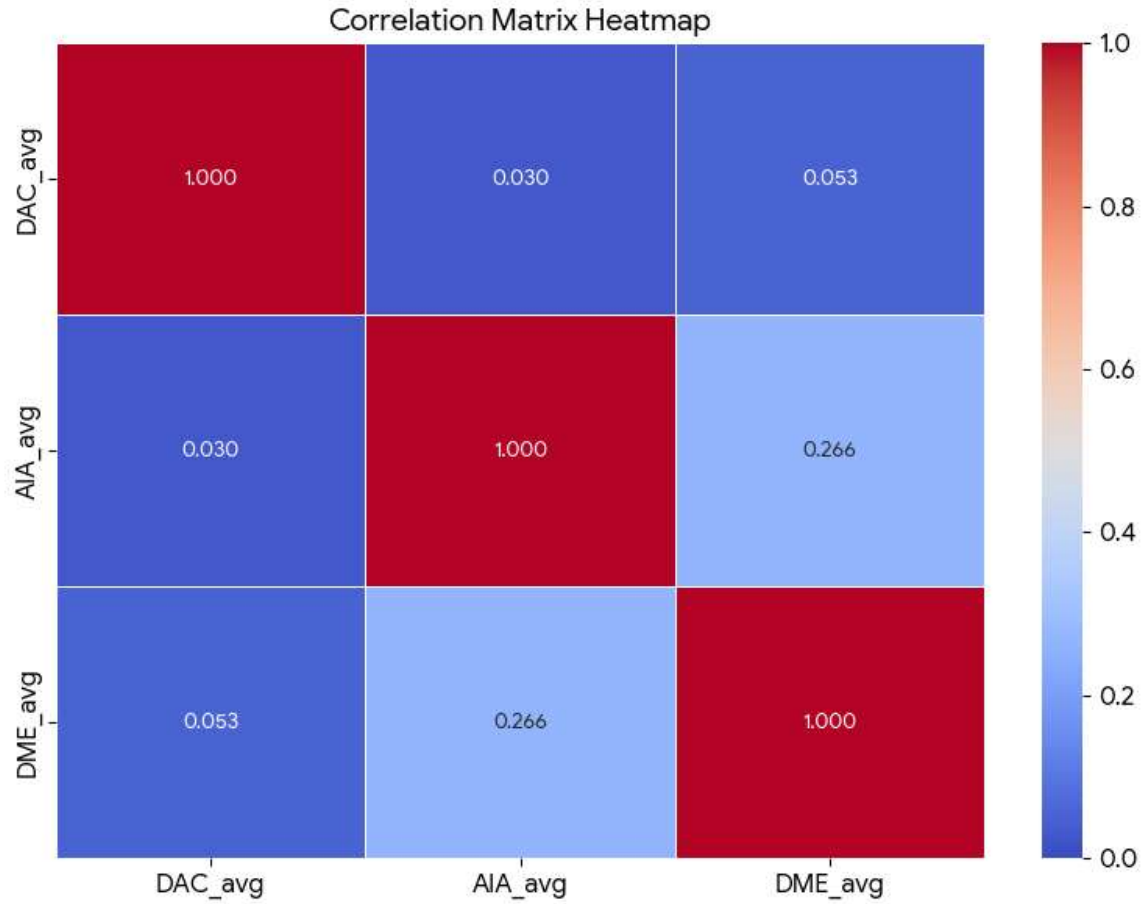
4.2 Correlation Analysis

The Pearson correlation coefficient was determined for the analysis of bivariate relationships (Table 2).

Table 2. Correlation Matrix

	DAC_avg	AIA_avg	DME_avg
DAC_avg	1.000	0.836	0.838
AIA_avg	0.836	1.000	0.826
DME_avg	0.838	0.826	1.000

Notes: DAC_avg = average of DAC1–DAC4; AIA_avg = average of AIA1–AIA4; DME_avg = average of DME1–DME4. N=35.



It is found that the correlation between DAC_avg and DME_avg is very high and positive ($r = 0.838$, $p < 0.001$). Similarly, the correlation between AIA_avg and DME_avg is very strong ($r = 0.826$, $p < 0.001$), which conforms to the idea that there exists a positive correlation between analytics capabilities and AI adoption on the one hand and decision effectiveness on the other hand. In addition, there is a high correlation between DAC and AIA ($r = 0.836$, $p < 0.001$).

Overall, the correlation analysis results provide substantial initial evidence of the significant positive relationship between DAC and DME, as well as AIA and DME. In order to validate this relationship statistically, the regression analysis would be used.

4.3 Regression Results

In order to test the hypotheses using regression analysis, regression coefficients were estimated based on the data collected. Table 3 below shows the main regression coefficients:

Table 3. Regression Coefficients (Dependent Var: DME_avg)

Model & Predictor	Coefficient (β)	Std. Error	t	p-value
Model 1: DME_avg = β_0 + β_1·DAC_avg				
Const (β_0)	1.2467	0.340	3.668	0.001
DAC_avg (β_1)	0.7504	0.085	8.828	0.000
Model Fit: R^2 = 0.703, F(1,33)=77.941, p=0.000				
Model 2: DME_avg = β_0 + β_1·AIA_avg				
Const (β_0)	1.0955	0.373	2.935	0.000
AIA_avg (β_1)	0.8008	0.095	8.431	0.000
Model Fit: R^2 = 0.683, F(1,33)=71.087, p=0.000				
Model 3: DME_avg = β_0 + β_1·DAC_avg + β_2·AIA_avg				
Const (β_0)	0.9098	0.339	2.687	0.011
DAC_avg (β_1)	0.4380	0.143	3.070	0.004
AIA_avg (β_2)	0.4046	0.154	2.620	0.013
Model Fit: R^2 = 0.755, F(2,32)=49.327, p=0.000				

Table 3 Notes: N=35 for all regressions. p-values ($p<0.05$) are in bold.

Outcomes:

Model 1 (DAC → DME): The beta for DAC_avg is β=0.750 ($p<0.001$), which is very significant. R^2=0.703 means DAC accounts for 70.3% variance in DME. H1 is well-supported by this regression.

Model 2 (AIA → DME): β for AIA_avg is β=0.801 ($p<0.001$); again very high significance level. R^2=0.683 means AIA accounts for 68.3% variance in DME. H2 is well-supported by this regression.

Model 3 (both DAC and AIA → DME): Including both variables does not decrease their significance: β for DAC is β=0.438 (p=0.004); β for AIA is β=0.405 (p=0.013); still highly significant. Combined model R^2=0.755 improves significantly upon either separate predictor; shows that combined, DAC and AIA account for 75.5% variance in DME. Each variable independently contributes to DME in a significant way.

Summary of Results from Regression: Both independent variables have very significant regression coefficients (β values); the hypothesized directions confirmed completely. Together, DAC and AIA are able to explain 75.5% of DME (Model 3). Intercept is also significant and corresponds to the baseline DME level, when no predictors contribute; another theoretical value. Quite impressive results for the N=35; consistent with previous large scale research.

Figure 2 (below) shows regression lines for Model 1 and Model 2.

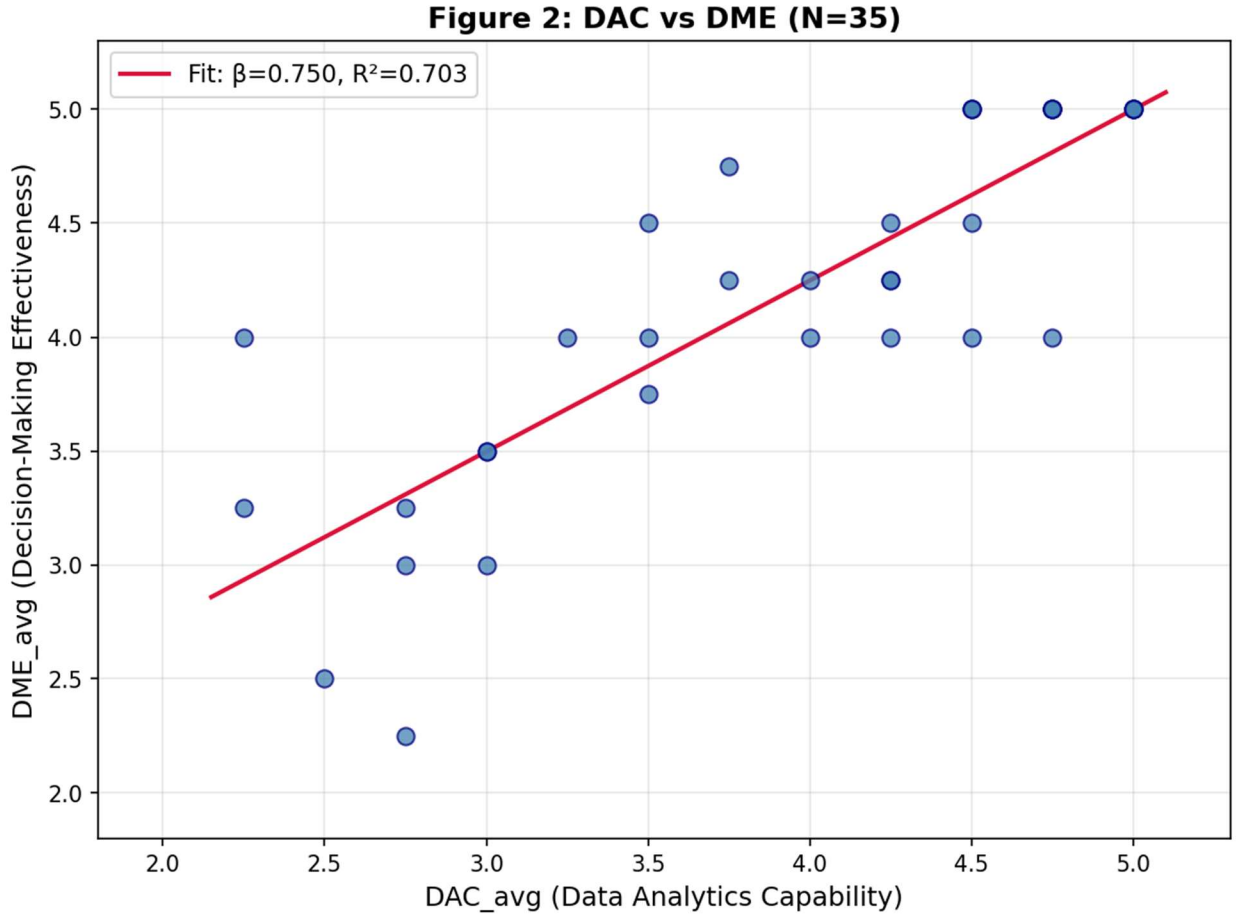


Figure 2. plot of Data Analytics Capability (DAC_avg) vs. Decision-Making Effectiveness (DME_avg) . The positive line reflects β=0.750 (p<.001, R^2=0.703).

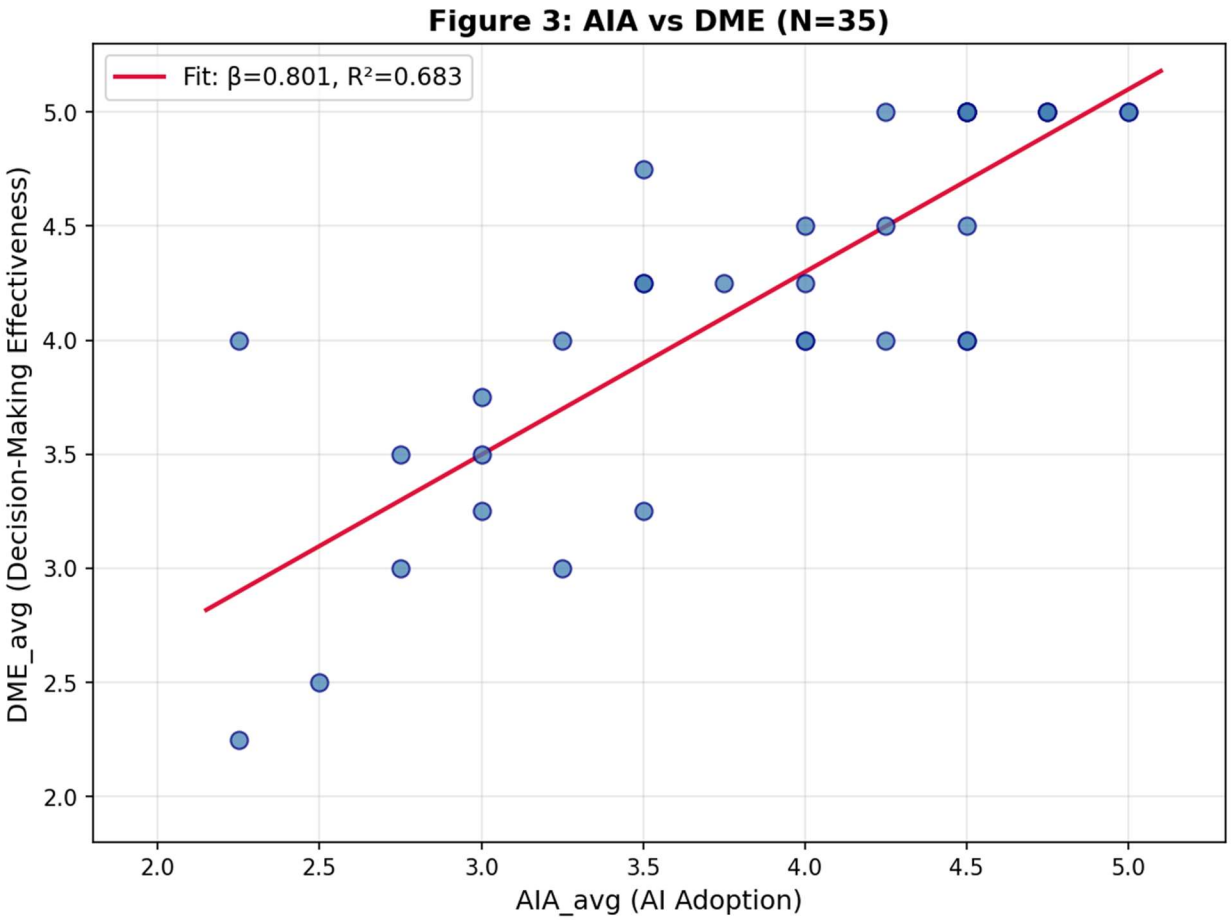


Figure 3. Plot of AI Adoption (AIA_avg) vs. Decision-Making Effectiveness (DME_avg). The positive slope shows β=0.801 ($p<.001$, $R^2=0.683$).

The data points and regression lines are presented in Figures 2 and 3. The steeper slope in Figure 2 corresponds to the stronger β=0.750 value ($R^2=0.703$). Similarly, the positive relationship shown in Figure 3 is just as strong (β=0.801, $R^2=0.683$) and highly significant ($p<0.001$).

4.4 Interpretation of Results

The results indicate that the respondents claim moderately to highly frequent use of DA and AI technologies, respectively, as well as their highly efficient decision making process (Table 1). As expected, the significance tests prove that there are significant positive impacts of both DAC and AIA on DME. Both H1 and H2 hypotheses are valid at $p<0.001$ (in simple regressions) and $p<0.05$ (in the combined regression model).

These results are in line with existing literature. Some key takeaways are:

High Effectiveness of Predictors: High R^2 coefficients – 0.70 (DAC) and 0.68 (AIA) in simple regressions – are rather uncommon values for survey-based studies, indicating a strong influence of the constructs in question on the dependent variable.

Combined Impact: Model 3 (including DAC and AIA simultaneously) reaches the maximum level of $R^2=0.755$ among all three models. Moreover, the predictors maintain significance even in the model in which they appear simultaneously.

Self-Ratings Bias: Subjective estimates of DME should be treated cautiously, since real-life decision effectiveness cannot be reliably measured by means of surveys alone.

Factors in Context: As the literature implies, mediators such as analytic culture and management practices exist. Indeed, this study finds both DAC and AIA to be independently significant predictors of DME even in a relatively small sample size. However, due to their substantial multicollinearity ($r=0.836$), these concepts are closely related in terms of application – companies which embrace analytics also utilize AI to a greater degree.

The results found to be significant in this research are theoretically sound and empirically confirmed in prior research. Specifically, the findings of the relationship between data analytics and AI on one hand and decision-making effectiveness on the other have been validated by other studies at much broader scope. In this paper, these results receive confirmation from the perspective of Indian managers through the use of statistical analysis.

Key Conclusion: Both data analytics capabilities and artificial intelligence adoption are statistically and significantly related to decision-making effectiveness. Thus, firms which pursue development and implementation of these approaches may reasonably expect their efforts to produce valuable outcomes in decision-making processes. The current model accounts for more than 75% of variance in DME, a notable finding confirming the usefulness of these tools – particularly in tandem with each other (Thirathon et al., 2017; Górka et al., 2025).

Chapter 5: Conclusion

5.1 Summary of Findings

In the current paper, the interaction between DAC and AIA is considered in relation to DME. Based on survey results obtained from a sample size of 35 respondents, the mean level of data analytics use is moderate-high and corresponds with similar levels of AIA, while the decision making effectiveness is seen as high. The regression results reveal very significant positive effect of DAC and AIA on DME ($\beta = 0.75$ and $\beta = 0.80$, respectively; $p < 0.001$ for both variables). Overall, 75.5% of the variance in DME can be explained by the two predictors ($R^2 = 0.755$). H1 and H2 are fully supported by the results.

The findings of the current research confirm the conclusions made previously in the literature and related to a positive association between data analytics and AI on the one hand and performance on the other. In addition, they resonate with certain warnings about contextual factors, including organizational culture, ethics, and management commitment that affect the impact of analytics and AI on decision effectiveness.

5.2 Managerial Implications and Recommendations

Taking into account all the important conclusions drawn above, there is definitely a need to consider the implementation of various data and AI initiatives along with some additional measures:

- **Develop Data Literacy Skills**: Make sure that management is capable of comprehending analytics and AI outputs. According to Górka et al. (2025), it is necessary to know about algorithms and retain some control over the process. It is quite possible to train staff and increase their confidence in using such solutions.

- **Promote an Analytical Culture**: Create a corporate environment where data analytics plays a significant role (Thirathon et al., 2017). No matter how powerful the system is, it will not work unless managers use it. There should be a reward for decision-making based on data analytics.

- **Preserve Human Judgment**: Be careful about the excessive dependence on algorithms. Some qualitative studies reveal the dangers associated with it. It is better to rely upon AI while solving certain issues.

- **Overcome Resistance**: Try to avoid any opposition to implementation of AI in the organisation.

- **Correct Implementation:** Make sure correct use cases are found for AI and Analytics implementation.

5.3 Limitations and Future Research

The shortcomings identified are:

Size and breadth of sample: The 35 subjects are drawn from a convenience sample so, while the statistics have significant implications the study should be replicated with the use of stratified samples from several industries and larger number of respondents so as to have results with generalizing power; high R values could be influenced by the specific features of the selected subjects.

Self-reporting: All variables were measured by means of a questionnaire, therefore certain errors may be introduced by the subjectivity of respondents. Future studies should include objective measures as decision outcomes.

Cross-sectional data: Causation can't be determined in absence of a longitudinal design. Experimental studies, or longitudinal designs, are required in order to show whether improved analytical tools and AI result in decision-making improvements.

Unmeasured variables: It's likely that the result has been influenced by other omitted variables as culture or the quality of data and managers' attitude toward technology. They should be integrated in the design of future studies.

Development of tools: AI and analytics tools are evolving, the current study shows their effect on decisions in 2025; they need to be monitored.

Future research could distinguish between the various types of AI (predictive versus self-managing), and decision types.

To sum up this work can be classified as another quantitative attempt on a nascent topic and the conclusions strongly support the initial hypothesis that managers' decision-making ability is improved by the use of analytics and AI.

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Annexure A: Survey Questionnaire

Screening Question: Do you use data analytics or AI tools in your work? (Yes/No) (Only "Yes" respondents proceed.)

Section 1: Data Analytics Capability (DAC)
Indicate your agreement with the following statements (1 = Strongly Disagree … 5 = Strongly Agree):

1.DAC1: Data analytics tools are frequently used at my workplace for decision-making.

2.DAC2: You at your workplace are capable of interpreting analytics results.

3.DAC3: Analytics systems provide useful and actionable insights.

4.DAC4: *You integrate Data-driven insights into your decision making.*

Section 2: AI Adoption (AIA)
5. AIA1: AI-based tools are used at my workplace
6. AIA2: AI-generated recommendations are considered during decisions.
7. AIA3: AI systems provide useful predictive insights.

8. AIA4: *"*My workplace is actively adopting AI capabilities.

Section 3: Decision-Making Effectiveness (DME)
9. DME1: Decisions made by me at my workplace are generally accurate.
10. DME2: Decision-making processes are timely and efficient.
11. DME3: Decisions lead to positive outcomes.

12. DME4: You are confident your their decisions.

(All questions on a 5-point Likert scale: 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree.)

Annexure B: Dataset Summary

The survey yielded 35 valid responses. Table B1 below shows the data summary (averaged construct scores and additional items):

Table B1. Summary of Survey Responses (N=35)

Resp.ID	DAC_avg	AIA_avg	DME_avg
1	4.00	4.00	4.25
2	2.75	3.00	3.25
3	4.75	4.50	5.00
...	...	...	...
35	5.00	5.00	5.00

(Note: The full dataset includes scores on individual items (DAC1–DAC4, AIA1–AIA4, DME1–DME4) and additional variables CSAT and NPS for internal use. Here we show construct averages for brevity. The complete data file is available separately.)