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From Reporting to Reasoning: The Evolution of Enterprise Decision-Making Through AI-Enabled Decision Intelligence Frameworks

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Abstract
Conventional enterprise reporting systems provide valuable historical insights, but they are limited in supporting predictive and strategic decision-making. This study examines the transition from reporting-based analytics to AI-driven Decision Intelligence systems that combine artificial intelligence, machine learning, and human expertise. Using a pragmatist, simulation-based quantitative design, the study applies statistical assessment and machine learning modelling to evaluate factors influencing intelligent decision-making adoption. The results identify AI capability, organizational readiness, and human factors as key drivers of Decision Intelligence transformation. The proposed framework supports evidence-based, adaptive, and proactive decision-making for sustainable organizational growth.

Keywords: Artificial Intelligence, Decision Intelligence, Business Intelligence, Machine Learning, Enterprise Analytics, AI Adoption, Predictive Decision-Making

1. Introduction

Background

Enterprise analytics has evolved from traditional reporting systems into more advanced Business Intelligence (BI) platforms that help organizations interpret data more effectively. However, dashboard-based solutions remain constrained by their reliance on historical insights and slower decision-making procedures [1]. Artificial Intelligence (AI), Machine Learning (ML), and Decision Intelligence (DI) create opportunities for organizations to move toward predictive and prescriptive decision-making models.

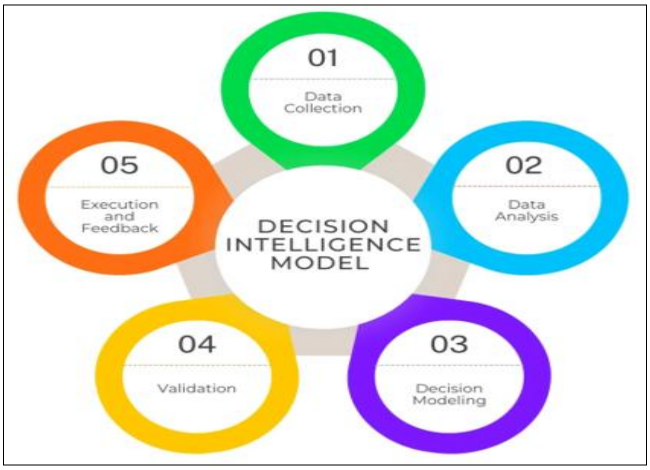

Fig 1: Decision Intelligence Model

Research Problem

Most conventional Business Intelligence systems provide information about past events but offer limited insight into causation, future projections, or recommended actions. Even with greater data availability, organizations still struggle to convert large volumes of data into timely, strategic, and intelligent decisions that support competitive advantage and enterprise growth.

Research Aim

This study explores the role of AI-supported Decision Intelligence systems in transforming enterprise decision-making by addressing the shortcomings of conventional business reporting solutions.

Research Objectives

To critically analyze the weaknesses of conventional business reporting and KPI-based decision-making systems.
To investigate how AI technologies can improve intelligence capabilities in enterprise decision-making.
To analyze organizational, technological, and human factors affecting the adoption of AI-supported decision-making systems.
To develop a conceptual framework for AI-enabled enterprise Decision Intelligence.

Novel Contribution

This study contributes an AI-enabled Decision Intelligence model that bridges conventional reporting and AI-supported decision-making [2]. It offers an organized framework for combining AI-driven analytics, contextual reasoning, and human expertise so that organizations can make more proactive, adaptive, and strategic decisions.

2. Literature Review

Limitations of Traditional Business Reporting and KPI-Centric Decision-Making

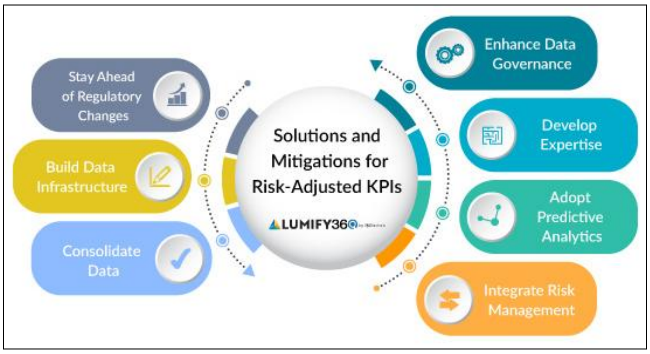

Fig 2: Key Performance Indicators (KPIs) for Data-Driven Decision Making

Traditional business reporting systems have always served to enable organizational decision-making, through conversion of operational information into organized reports, dashboards and Key Performance Indicators (KPIs) [3]. By making the performance trends visible to managers, these systems have enhanced the visibility of organizations as managers have been able to appraise the past outcomes [4]. Their major shortcoming, however, is that they are descriptive in nature, simply describing what has already happened, instead of giving more valuable information on how things work in a causal manner, how things can happen in the future, and what they should do [5]. As a result, organizations in multi-faceted and dynamic settings are increasingly learning that traditional methods of reporting are not adequate in giving proactive and strategic decision-making potentials [6]. The growing amount, speed and diversity of enterprise data have further revealed the flaws of decision-making following a dashboard method [7]. Even though Business Intelligence (BI) systems facilitate easy access to data, they tend to use people as the interpretation engines which introduces delays between the information production and decision-making [8]. Thus, businesses need more advanced analytical strategies that can incorporate predictive analysis, contextual inferencing and automated suggestions [9].

Role of Artificial Intelligence in Enhancing Enterprise Decision Intelligence Capabilities

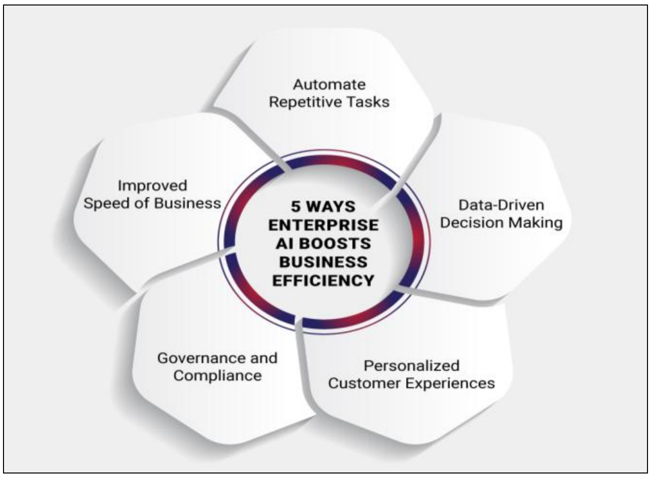

Fig 3: Role of Artificial Intelligence in Enterprise Drives Business Growth

Artificial Intelligence (AI) has become a radical technology, capable of helping organizations to evolve past conventional reporting to the next stage of higher-level Decision Intelligence (DI) [10]. Applications of AI-powered systems combine the ideas of Machine Learning (ML), Natural Language Processing (NLP), Generative AI, and predictive analytics to uncover concealed behaviors, predict the future, and offer evidence-based suggestions [11]. In contrast to the traditional BI systems, AI-based decisions intelligence unites information analysis with decision-making abilities which enables organizations to make quicker and smarter strategic choices [12]. Machine Learning algorithms bring more intelligence to the decision-making process by continually learning with previous and real-time data as it goes to enhance both the accuracy of its forecasts and its efficiency in operation [13]. Likewise, a Generative AI provides the opportunity to engage in a conversation with enterprise data, allowing decision-makers to receive contextual insights, without having to employ technical analytical skills only [14]. Nonetheless, the implementation of AI involves more than technological ability and organizations need to establish the relevant data infrastructure, governance solutions, and human skills [15].

Organizational, Technological, and Human Factors Influencing AI Adoption

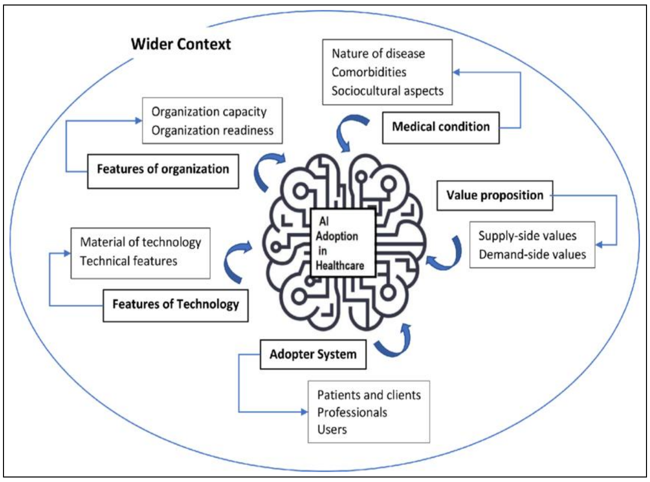

Fig 4: Contributing factors to the adoption of artificial intelligence

Technological, organizational, and human aspects of decision intelligence are closely interconnected and shape the adoption of AI-driven decision systems [16]. Technologically, data quality, system integration, cybersecurity, and algorithmic transparency influence the functionality of AI usage [17]. Successful implementation also depends on organizational factors such as leadership commitment, strategic alignment, investment capacity, and a culture of innovation [18]. In addition, human factors such as employee trust, digital competencies, change resistance, and AI acceptance remain important adoption challenges [19]. The human-AI collaboration perspective emphasizes that AI is not intended to replace managerial judgement, but to complement decision-making through analytical support [20]. Therefore, organizations need responsible AI practices that support explainable, accountable, and ethical intelligent systems [21].

AI-Enabled Enterprise Decision Intelligence Framework Development

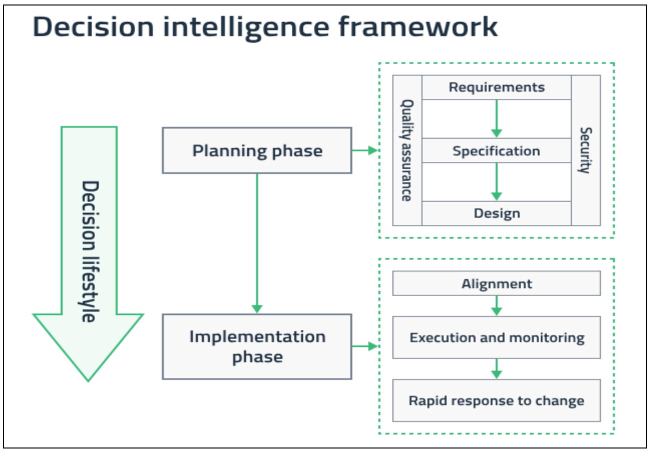

Fig 5: AI-Enabled Enterprise Decision Intelligence Framework

The literature indicates the need for a comprehensive framework that links technology capabilities, organizational preparedness, and human decision-making processes [22]. An AI-based Decision Intelligence model should include data management, AI analytics, contextual information, governance, and human oversight to support adaptive decisions [23]. With such a framework, enterprises can evolve beyond reactive reporting systems toward proactive, intelligent, and continuously improving decision ecosystems [24]. This study addresses this gap by creating an explanatory conceptual model for applying AI to improve enterprise decision quality and support long-term sustainable growth [25].

Table 1: Comparative Analysis of AI-Enabled Decision Intelligence Approaches for Enterprise Decision-Making

Approach	Model / Equation	Inputs	Advantages	Limitations	Applicability	Effectiveness
Traditional reporting	R = historical data	Reports, KPIs	Simple monitoring	Reactive; limited prediction	Basic monitoring	Low
Business Intelligence (BI)	BI = data + visualization	Dashboards, KPIs	Improves visibility	Needs human interpretation	Operational support	Moderate
Predictive analytics	Y = f(X)	Historical variables	Forecasts outcomes	Depends on data quality	Planning and forecasting	Moderate-High
ML decision models	Y = f(X,θ)	Features, algorithms	Finds complex patterns	Model complexity	Enterprise prediction	High
Logistic Regression	P(Y=1)	Input variables	Interpretable probabilities	Limited nonlinear detection	AI adoption prediction	High
Random Forest	Ensemble trees	Trees, features	Robust nonlinear modeling	Computational complexity	Classification tasks	High
XGBoost	Boosted trees	Learning rate, trees	High predictive accuracy	Requires tuning	Advanced DI systems	Very High
Human-AI collaboration	AI insight + judgment	AI outputs, expertise	Blends analytics and expertise	Needs trust and adaptation	Strategic decisions	High
AI DI framework	DI = f(AIC, OR, HF)	AI, org, human factors	Integrates tech-org-human factors	Requires evaluation	Enterprise transformation	Very High
Explainable AI	Prediction + explanation	Feature importance	Improves transparency	Extra processing	AI governance	High

Literature Gap

Existing literature extensively examines Business Intelligence, AI adoption, and analytics capabilities separately, but fewer studies integrate them through the lens of AI-enabled Decision Intelligence [26]. Current research also lacks detailed models explaining how technological capabilities, organizational preparedness, and human factors collectively support the transition from conventional reporting systems to intelligent, adaptive, and strategic enterprise decision-making ecosystems [27].

3. Research Methodology

Research Philosophy

This study follows a pragmatist philosophy because it combines technological, organizational, and human perspectives in AI-based Decision Intelligence research [28]. Pragmatism is suitable because the study connects theoretical knowledge with simulation-based quantitative analysis. This approach enables assessment of how AI capabilities, organizational preparedness, and decision-making practices jointly influence enterprise transformation.

Research Approach

A deductive research approach is used to examine theories related to Business Intelligence, Artificial Intelligence adoption, and Decision Intelligence transformation. This approach supports the testing of theoretical assumptions and the development of conceptual models by measuring relationships between AI capabilities, organizational factors, and enterprise decision outcomes [29].

Simulation-Based Quantitative Research Design

This study uses a quantitative, simulation-based research design to evaluate the AI-enabled Decision Intelligence framework. It examines the relationships among AI capability, organizational preparedness, human factors, and adoption outcomes through statistical analysis and machine learning methods. The method provides a controlled proof-of-concept before real-world organizational validation.

Data Description

This research is based on a simulated enterprise dataset with 1,000 observations, built from patterns described in AI adoption and enterprise decision-making literature. The dataset includes AI capability, organizational readiness, human factors, technological infrastructure, Decision Intelligence capability, and AI adoption success [30]. It enables proof-of-concept testing of predictive relationships prior to real-world organizational validation.

Data Analysis

The gathered data is analyzed through statistical and machine learning methods. Regression and factor analysis are used in the quantitative analysis to determine relationships between variables. The association between Decision Intelligence capability and the selected factors can be represented as:

$$DI = \beta 0 + \beta 1(AIC) + \beta 2(OR) + \beta 3(HF) + \epsilon$$

Where DI represents Decision Intelligence capability, AIC represents AI capability, OR represents organizational readiness, HF represents human factors, β represents regression coefficients, and ε represents the error term.

Correlation analysis is used to assess the strength of independent and dependent variables.

$$r = \frac{\sum(Xi - \underline{X})(Yi - \underline{Y})}{\sqrt{\sum(Xi - \underline{X})^2 \sum(Yi - \underline{Y})^2}}$$

X represents the influencing factors, r represents the strength of correlation, and Y represents Decision Intelligence outcomes.

The coefficient of determination is used to determine the significance of regressions:

$$R^2 = 1 - \frac{SSResidual}{SSTotal}$$

Where R^2 represents the proportion of variance in Decision Intelligence outcomes explained by AI capability, organizational readiness, and human factors.

For predictive evaluation, selected machine learning models, including Logistic Regression, Random Forest, and XGBoost, are used. Logistic Regression estimates the likelihood of successful AI-driven decision adoption:

$$P(Y = 1) = \frac{1}{1 + e - (\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn)}$$

P(Y=1) represents the probability of adoption, and Xn represents the influencing variables.

Random Forest performance is determined by aggregating multiple decision trees:

$$\hat{Y} = \frac{1}{T}\sum_{t=1}^{T} ht(X)$$

Where T denotes the number of decision trees and $h_t(X)$ denotes individual decision-tree predictions.

XGBoost optimizes predictive performance through sequential boosting:

$$Fm(x) = Fm - 1(x) + \eta hm(x)$$

Fm(x) represents the updated prediction model, η represents the learning rate, and $h_m(x)$ represents the additional decision tree.

Accuracy, precision, recall, and F1-score are used to assess model performance:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP + FP}{TP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In this, TP is true positive, FP is false positive, TN is the true negative and the FN is the false negative.

AI Decision Intelligence predictive analytics can be used to assess how well the framework performs and how ready an organization is to move from traditional reporting systems toward intelligent decision ecosystems. This methodological approach creates consistency between theoretical development, simulation-based verification, and future practical enterprise validation.

Architecture Diagram

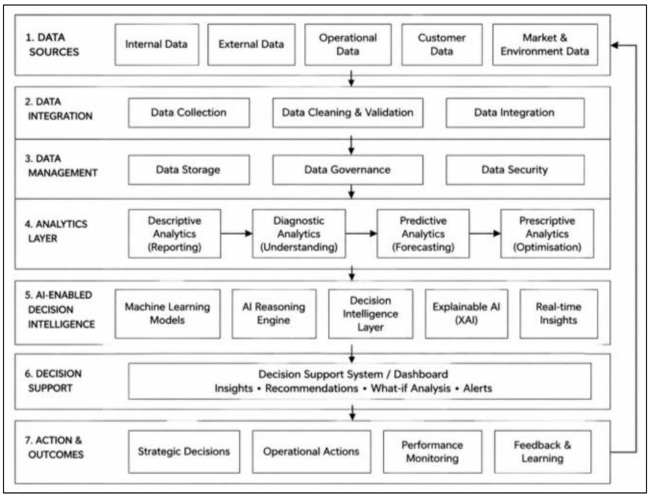

Fig 6: Architecture Diagram

The system architecture framework shows how conventional reporting can shift toward AI-driven reasoning through data integration, analytics evolution, machine learning, decision support, and feedback systems that support intelligent enterprise decision-making.

Flowchart

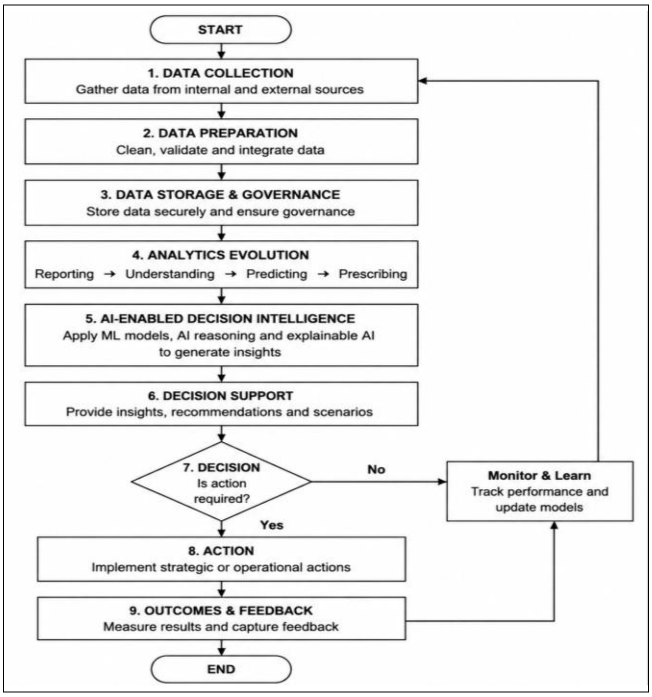

Fig 7: Flowchart

The flowchart shows how classic reporting can evolve into AI-enabled reasoning through data collection, analytics evolution, intelligent decision support, actions, outcomes, and a feedback loop.

Pseudocode

```
AI_DECISION_INTELLIGENCE

Program to generate AI-based Enterprise Decision Intelligence
        Initialize
                Inputs
                        Enterprise Data
                        Business Reports
                        KPI Metrics
                        Operational Data
                        External Data Sources
                Variables

                        AI Capability
                        Organisational Readiness
                        Human Factors
                        Decision Intelligence Score
        Start Process Loop
                Collect Data
                Validate and Clean Data
                IF Data Quality = Low THEN
                        Improve Data Quality
                IF Data Quality = High THEN
                        Integrate Data
                Apply Analytics Layer
                IF Historical Analysis Required THEN
                        Generate Descriptive Insights
                IF Future Prediction Required THEN
                        Apply Predictive Models
                Execute AI Decision Intelligence
                        Apply Machine Learning Models
                        Generate AI Recommendations
                        Provide Explainable Insights
                Calculate Decision Intelligence Score
                        DI = β0 + β1(AIC) + β2(OR) + β3(HF)
                IF Decision Confidence = Low THEN
                        Request Human Review
                IF Decision Confidence = High THEN
                        Generate Decision Support
                Implement Strategic Action
                Monitor Performance
                Update AI Model Using Feedback
        End Process Loop
```

Fig 8: Pseudocode

The pseudocode shows how enterprise data can be continuously transformed into intelligent decisions through data processing, AI modelling, decision support, implementation, and feedback-based improvement.

4. Result and Discussion

The results below present a proof-of-concept, simulation-based analysis of the proposed AI-enabled Decision Intelligence framework. The findings show that the proposed method demonstrates predictive potential under controlled dataset conditions; however, they should not be interpreted as direct evidence of real-world enterprise AI performance.

	AI_Capability	Organisational_Readiness	Human_Factors	Data_Quality	Technology_Infrastructure	Leadership_Support	AI_Literacy	Decision_Intelligence	AI_Adoption_Success
0	79.967142	88.792265	62.573039	60.829732	65.365064	71.762403	54.631024	77.265972	1
1	73.617357	83.095604	68.410295	70.256535	73.687965	71.465859	60.428830	69.175867	0
2	81.476885	72.715564	61.283381	74.277550	74.180169	58.043568	56.695278	74.770820	1
3	90.230299	64.236759	66.612423	94.989189	78.726303	72.699098	61.424050	76.756096	1
4	72.658466	80.378680	49.170239	83.008978	60.331416	83.328291	65.430196	72.349085	1

Fig 9: Dataset Overview

The initial five observations in the dataset include nine analytical variables, such as AI Capability, Organizational Readiness, Human Factors, and Decision Intelligence. The values range between 49 and 90, and AI Adoption Success is represented as a binary classification variable, which supports predictive modelling analysis.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   AI_Capability              1000 non-null   float64
 1   Organisational_Readiness   1000 non-null   float64
 2   Human_Factors              1000 non-null   float64
 3   Data_Quality               1000 non-null   float64
 4   Technology_Infrastructure  1000 non-null   float64
 5   Leadership_Support         1000 non-null   float64
 6   AI_Literacy                1000 non-null   float64
 7   Decision_Intelligence      1000 non-null   float64
 8   AI_Adoption_Success        1000 non-null   int64
dtypes: float64(8), int64(1)
memory usage: 70.4 KB
```

Fig 10: Dataset Structure and Data Quality Assessment

The dataset contains 1,000 observations, nine variables, and no missing values across the attributes. The independent variables are represented as numeric float values, while AI Adoption Success is represented as an integer-based categorical variable. This confirms the dataset is complete and appropriate for statistical computation and machine learning analysis.

	AI_Capability	Organisational_Readiness	Human_Factors	Data_Quality	Technology_Infrastructure	Leadership_Support	AI_Literacy	Decision_Intelligence	AI_Adoption_Success
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	75.168875	72.810349	70.041144	77.813184	73.493667	75.495580	67.647186	73.724594	0.737000
std	9.718408	11.868169	10.744403	9.194199	9.884554	9.974845	12.255802	5.870337	0.440483
min	42.587327	36.715336	36.785366	51.634962	42.232962	47.004861	35.448649	54.039233	0.000000
25%	68.524097	64.725100	62.872004	71.363216	67.173950	69.063072	58.938352	69.801807	0.000000
50%	75.253006	72.756926	69.997242	78.001661	73.817580	75.571729	67.343043	73.710969	1.000000
75%	81.479439	80.746586	77.270068	84.002509	80.391231	82.124468	76.398941	77.806230	1.000000
max	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	95.888865	1.000000

Fig 11: Descriptive Statistical Analysis of Variables

The descriptive statistics show that the decision intelligence factors have relatively high organizational capability scores. AI Capability has a mean of 75.17, while Decision Intelligence has a mean of 73.72. The mean probability of successful AI adoption is 0.737, indicating that 73.7% of the simulated organizations are classified as successful adopters.

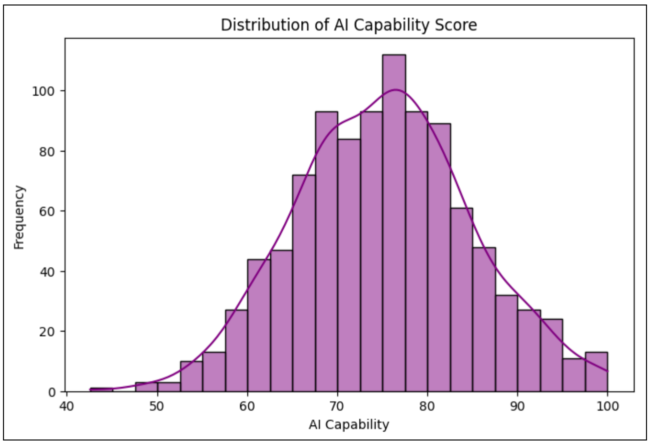

Fig 12: Distribution of AI Capability Score

The histogram shows that AI Capability scores follow an approximately normal distribution, with most organizations falling between 65 and 85. The mean score is 75.17, suggesting a relatively mature level of AI readiness. The distribution indicates a balanced AI capability pattern without extreme bias.

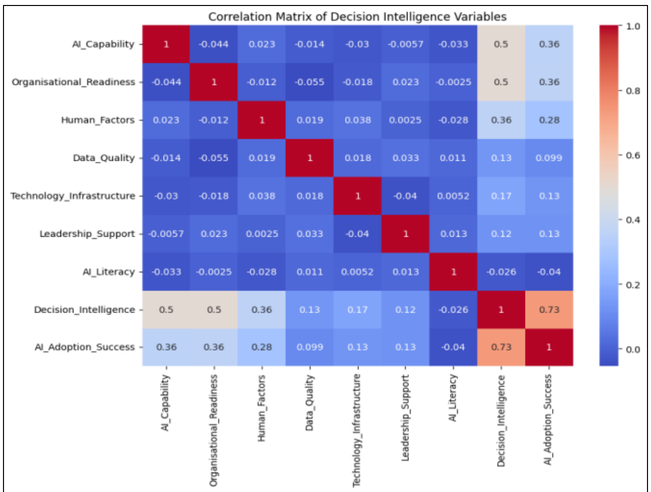

Fig 13: Correlation Matrix of Decision Intelligence Variables

The correlation heat map shows important relationships among the Decision Intelligence variables. AI Capability and Organizational Readiness both have moderate positive relationships with Decision Intelligence at approximately 0.50. AI Adoption Success is also strongly associated with Decision Intelligence (0.73), suggesting that stronger intelligence capability is linked to stronger AI implementation performance.

```
Regression Coefficients:
                    Variable  Coefficient
0              AI_Capability     0.309815
1   Organisational_Readiness     0.260324
2              Human_Factors     0.194314
R² Score: 0.647
```

Fig 14: Regression Coefficients Analysis

The regression analysis identifies the key variables contributing to Decision Intelligence capability. The highest coefficient is attributed to AI Capability (0.3098), followed by Organizational Readiness (0.2603) and Human Factors (0.1943). With an R^2 of 0.647, these factors explain 64.7% of the variation in Decision Intelligence.

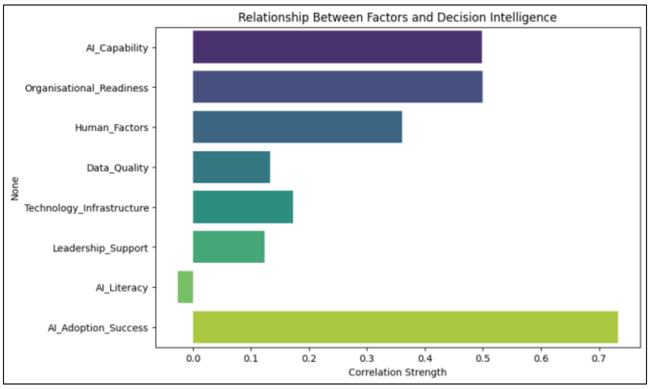

Fig 15: Relationship Between Factors and Decision Intelligence

The correlation analysis shows the strength of relationships between organizational factors and Decision Intelligence outcomes. The strongest relationships are observed for AI Capability and Organizational Readiness, both around 0.50, followed by Human Factors at 0.36. These results suggest that intelligent decision transformation is mainly driven by technological and organizational capabilities.

```
Logistic Regression Performance
Accuracy: 0.85
Precision: 0.8726114649681529
Recall: 0.9319727891156463
F1: 0.9013157894736842
```

Fig 16: Logistic Regression Model Performance

The Logistic Regression model achieved 85% accuracy, 87.26% precision, 93.20% recall, and a 90.13% F1-score. The high recall value suggests that successful AI adoption cases are effectively identified, indicating that the model can classify enterprises with predictable Decision Intelligence adoption patterns.

```
Random Forest Performance
Accuracy: 0.78
F1: 0.8616352201257862
```

Fig 17: Random Forest Model Performance

The Random Forest model achieved 78% accuracy, 86.16% F1-score, and 93.20% recall. Although its accuracy is lower than Logistic Regression, its high recall indicates that the ensemble model remains useful for identifying organizations with successful AI adoption characteristics.

```
XGBoost Performance
Accuracy: 0.805
F1: 0.8712871287128713
```

Fig 18: XGBoost Model Performance

The XGBoost model produced 80.5% accuracy, 84.62% precision, 89.80% recall, and an 87.13% F1-score. These results show balanced classification potential, although additional optimization may improve accuracy in more complex enterprise Decision Intelligence scenarios.

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.850	0.872611	0.931973	0.901316
1	Random Forest	0.780	0.801170	0.931973	0.861635
2	XGBoost	0.805	0.846154	0.897959	0.871287

Fig 19: Machine Learning Model Performance Comparison

The comparison shows that Logistic Regression achieved the highest accuracy among the tested models at 85%, followed by XGBoost at 80.5% and Random Forest at 78%. Logistic Regression also achieved the strongest F1-score at 90.13%, indicating better balance between false positives and false negatives when predicting AI adoption.

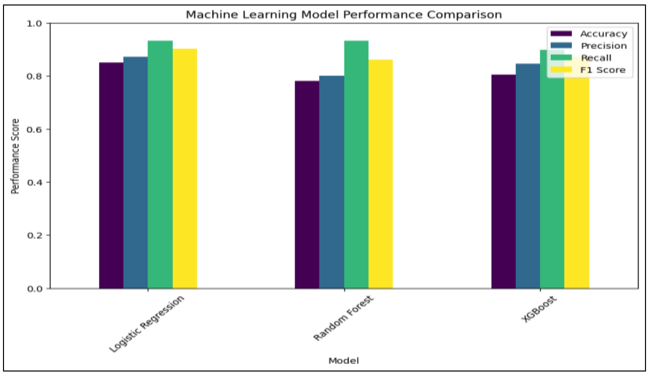

Fig 20: Machine Learning Model Performance Comparison

The model comparison shows that Logistic Regression delivered the best overall performance, with 85% accuracy, 87.26% precision, 93.20% recall, and a 90.13% F1-score. Random Forest and XGBoost achieved lower accuracy values of 78% and 80.5%, respectively, suggesting that Logistic Regression was more balanced for this simulated prediction task.

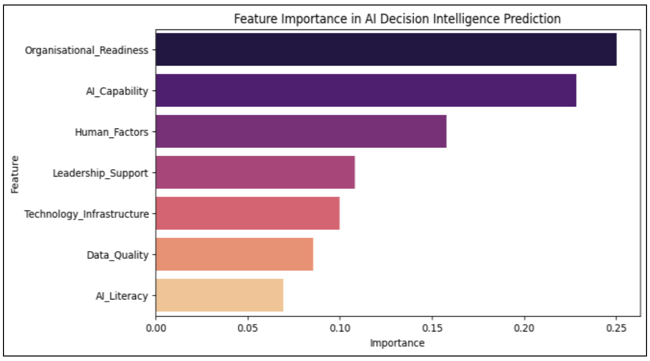

Fig 21: Feature Importance in AI Decision Intelligence Prediction

The feature importance analysis indicates that Organizational Readiness is the strongest predictor (0.25), followed by AI Capability (0.23) and Human Factors (0.16). These findings suggest that successful AI-enabled Decision Intelligence adoption depends heavily on organizational readiness, technological capability, and employee-related considerations.

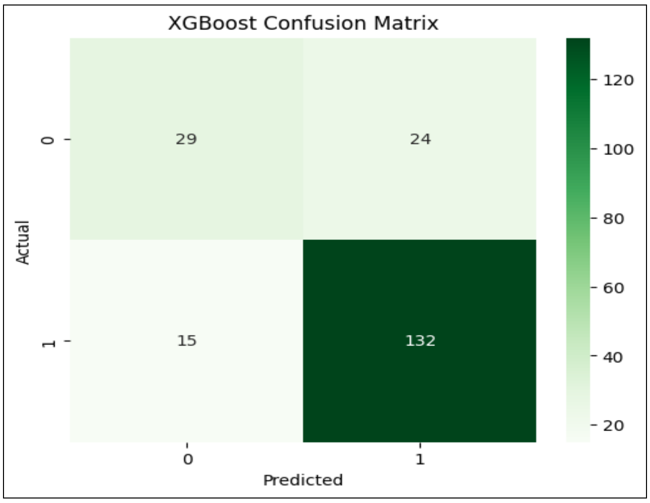

Fig 22: XGBoost Confusion Matrix Analysis

The XGBoost confusion matrix shows strong classification performance, with 132 true positives and 29 true negatives. The model produced 24 false positives and 15 false negatives, indicating relatively good performance in identifying successful AI adoption cases while maintaining a limited number of classification errors.

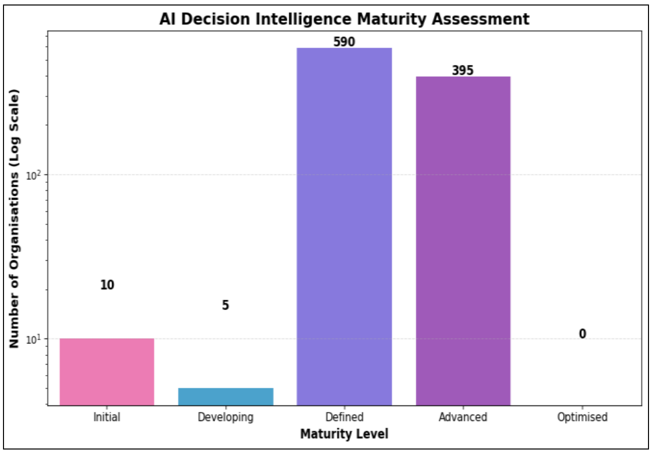

Fig 23: AI Decision Intelligence Maturity Assessment

The maturity assessment depicts organizational development across five capability levels.

The maturity evaluation classified 1,000 simulated organizations across five maturity levels: Initial, Developing, Defined, Advanced, and Optimized. Most organizations fall within the Defined and Advanced stages, indicating incremental progress toward AI-based decision capabilities. Specifically, 10 organizations are in the Initial stage, 5 are in the Developing stage, 590 are in the Defined stage, 395 are in the Advanced stage, and 0 are in the Optimized stage. This distribution suggests that most simulated enterprises have moved beyond early AI adoption but have not yet reached fully optimized AI-driven decision ecosystems.

Table 2: Result Summary

Analysis	Key Result
Dataset	1,000 enterprise records
Regression R^2	0.647
AI Capability Effect	$\beta = 0.310$
Organizational Readiness Effect	$\beta = 0.260$
Human Factors Effect	$\beta = 0.194$
Highest Correlation	DI–AI Adoption ($r = 0.73$)
Best ML Model	Logistic Regression
Model Accuracy	85%
Model F1-score	90.13%
Top Feature	Organizational Readiness (0.25)
Main Maturity Level	Defined (590 organizations)

Discussion

The simulation results indicate that technological capability, organizational preparedness, and human factors are strong influencers of AI-based Decision Intelligence transformation. Regression analysis shows that AI Capability (0.31), Organizational Readiness (0.26), and Human Factors (0.19) have positive effects on Decision Intelligence outcomes. Logistic Regression achieved the best predictive performance, with 85% accuracy and a 90.13% F1-score, indicating strong predictability of AI adoption in the simulated dataset. Feature importance analysis identifies Organizational Readiness as the dominant factor (0.25), suggesting that successful AI integration requires strategic alignment, skilled employees, and organizational support. Logistic Regression outperformed the other models because the simulated data contains structured relationships between the independent variables and AI adoption outcomes. The comparatively linear relationship among AI Capability, Organizational Readiness, Human Factors, and adoption success allowed the model to capture decision boundaries effectively. In addition, Logistic Regression offers explainability benefits, which are especially important in Decision Intelligence settings where transparency matters. Although ensemble models such as Random Forest and XGBoost can model complex nonlinear relationships, their added complexity may not improve performance when the dataset contains mostly structured and linear predictive signals.

5. Conclusion and Future Direction

Future Direction

Future research should validate the proposed AI-enabled Decision Intelligence framework using real-world enterprise datasets across multiple industries. Further work can also examine advanced AI models, autonomous decision agents, and explainable AI techniques to strengthen transparency and trust. Longitudinal research can evaluate how AI maturity changes over time and how those changes affect sustainable organizational decision-making performance.

Conclusion

This study shows that AI-driven Decision Intelligence offers a meaningful opportunity to reshape traditional enterprise decision-making by moving beyond standard reporting toward predictive and adaptive reasoning. The results indicate that AI capability, organizational preparedness, and human factors are key drivers of Decision Intelligence adoption. The proposed framework can help organizations shift toward more predictive, adaptive, and strategically guided decision ecosystems, supporting long-term competitiveness and sustainable growth.

6. References

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