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AI AND MACHINE LEARNING IN STRATEGIC BUSINESS DECISION-MAKING

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Abstract:

This study explores the impact of machine learning on strategic business decision-making through a robust methodology. Data was gathered from over 500 companies via online surveys, 15 industry experts through in-depth interviews, and public discussions analyzed using advanced text mining techniques. Rigorous data preprocessing, including cleansing, transformation, integration, feature selection, and discretization, ensured high-quality analysis. Multiple linear regression was used to quantify the influence of AI input, enterprise size, and the number of AI projects on business performance, resulting in a predictive equation. Enterprises were categorized into three clusters—Start-ups, Mid-Sized Tech Businesses, and Large Industry Leaders—through K-means clustering, highlighting differences in AI usage and performance. A decision tree model, developed with the C4.5 algorithm and validated through cross-validation, demonstrated strong predictive capabilities with high accuracy, recall, and F1 scores. This model identified scenarios where AI application significantly affects business outcomes, offering actionable insights for optimizing AI strategies. The findings corroborate existing literature and emphasize the positive impact of AI on enhancing strategic decision-making across various types of enterprises.

Keywords: *Machine Learning, Strategic Decision-Making, AI Impact, Business Performance, K-Means Clustering, Decision Tree Model.*

1. Introduction

In recent years, machine learning (ML) has emerged as a transformative force in strategic business decision-making, reshaping how organizations approach complex problems and leverage data. As businesses increasingly adopt AI technologies to enhance their operational efficiency and competitive edge, understanding the precise impact of these technologies on decision-making processes becomes crucial. This study investigates the influence of machine learning on strategic business decisions by employing a multi-faceted methodology that integrates diverse data sources and analytical techniques. The research involves gathering extensive data through online surveys from over 500 companies, conducting in-depth interviews with 15 industry experts, and analyzing public discourse on machine learning via advanced text mining methods. The study's rigorous data preprocessing—comprising cleansing, transformation, integration, feature selection, and discretization—ensures the reliability and validity of the results. Through multiple linear regression, the study quantifies how variables such as AI input, enterprise size, and the number of AI projects impact business performance. Furthermore, K-means clustering classifies enterprises into distinct groups, and a decision tree model, validated

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through cross-validation, provides actionable insights into AI's strategic applications. This research contributes to the growing body of knowledge on AI's role in enhancing decision-making and offers practical implications for optimizing AI strategies across different types of enterprises.

2. Methodology

The methodology for this study was designed to ensure the collection of high-quality and reliable data, focusing on the integration of AI and machine learning in strategic business decision-making. The data collection process involved several key stages. First, an online questionnaire was distributed across various industries, targeting decision-makers from over 500 enterprises. This questionnaire aimed to understand how companies are incorporating machine learning into their business strategies and operations. To complement this quantitative data, in-depth interviews were conducted with 15 business leaders and experts from diverse industries, providing valuable insights and practical experiences regarding the evaluation and application of machine learning techniques in business contexts. Additionally, public discussions about machine learning on social media platforms and online forums were analyzed using natural language processing and text mining techniques. This analysis helped capture broader public and industry sentiments about the role of machine learning in business.

Data preprocessing was a crucial step, involving several stages to convert raw data into a format suitable for analysis. This included data cleansing, which addressed incomplete, inaccurate, or inconsistent data by removing duplicates, filling in missing values, and correcting logical inconsistencies. Data transformation involved normalizing, standardizing, and encoding the data to facilitate analysis. The data was then integrated into a unified framework, ensuring consistency and comparability across different data sources, including surveys, interviews, and social media analysis. Feature selection and extraction were employed to focus the analysis on the most relevant aspects of business decision-making, using techniques like principal component analysis to reduce dimensionality. Finally, data discretization transformed continuous data into discrete categories, such as classifying companies into "small," "medium," and "large" groups, to facilitate group comparisons. This comprehensive approach to data collection and preprocessing was essential for deriving meaningful insights into the influence of AI and machine learning on strategic business decision-making..

3. Result & Discussion

Table 1 Regression analysis

Variables	Coefficient	Standard error	T-value	p value
Intercept	50.23	4.12	12.18	< 0.001
AI input	0.78	0.05	15.60	< 0.001
Enterprise size	3.42	0.87	3.93	0.0002
Number of AIprojects	1.29	0.32	4.03	0.0001

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Based on the regression analysis presented in Table 1, the multiple linear regression equation (Formula 1) for forecasting business performance indicators is as follows:

Business Performance Indicators = 50.23 + 0.78 × (AI Input) + 3.43 × (Enterprise Size) + 1.29 × (Number of AI Projects)
(1)

This equation quantifies the impact of AI input, enterprise size, and the number of AI projects on business performance metrics.

Cluster analysis

In this study, the K-means clustering method was employed to categorize enterprises based on factors such as AI input, business performance indicators, enterprise size, and the number of AI projects. This approach highlights the commonalities and differences in AI application across various types of enterprises. Python was utilized to carry out the cluster analysis, revealing distinct patterns and insights into how different enterprises leverage AI and machine learning in their strategic decision-making processes.

1. The script code is as follows

```
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
Into the features = data [[' AI ', 'business performance indicators',' scale ', 'AIproject
number']
labels = kmeans.labels_
data['Cluster'] = labels
print(" Cluster Center :")
print(kmeans.cluster_centers_)
```

2. The Output

Table 2 Cluster 1: Start-ups

S. No.	AI Input	Business performance indicator	Business size	Number of AIprojects
1	100	50	10	5
2	150	52	12	6
3	200	55	15	7
...	...	...	...	...
87	0	8	1	0

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Table 3 Cluster 2 Mid-sized technology-oriented enterprises.

S. No.	AI Input	Business performance metrics	Enterprise scale	Number of AIprojects
1	1000	75	30	15
2	1150	78	35	18
3	1300	80	38	20
...	...	...	...	...
217	0	10	3	0

Table 4 Cluster 3: Large industry leaders

S. No.	AI Input	Business performance metrics	Business size	Number of AIprojects
1	2000	90	45	25
2	2200	92	48	28
3	2400	95	50	30
...	...	...	...	...
196	260	20	16	6

Based on Table 2-4, enterprises are categorized into three clusters:

Cluster 1: Start-ups

- **AI Input:** Low
- **Performance:** Moderate
- **Size:** Small
- **AI Projects:** Few
- **Description:** Small, early-stage companies with limited AI investments and basic projects.

Cluster 2: Mid-Sized Tech Businesses:

- **AI Input:** Medium
- **Performance:** High
- **Size:** Medium
- **AI Projects:** Moderate
- **Characteristics:** Technology-focused companies actively using AI to enhance performance.

Cluster 3: Large Industry Leaders:

- **AI Input:** High
- **Performance:** High
- **Size:** Large
- **AI Projects:** Numerous
- **Characteristics:** Major industry players with extensive AI investments and significant success.

The study evaluates AI's impact on decision-making using features like AI usage in sales, risk assessment, and supply chain management, with performance categorized into High, Medium, and Low. The decision tree model, built using the C4.5 algorithm in Scikit-Learn, is shown in Figure 1.

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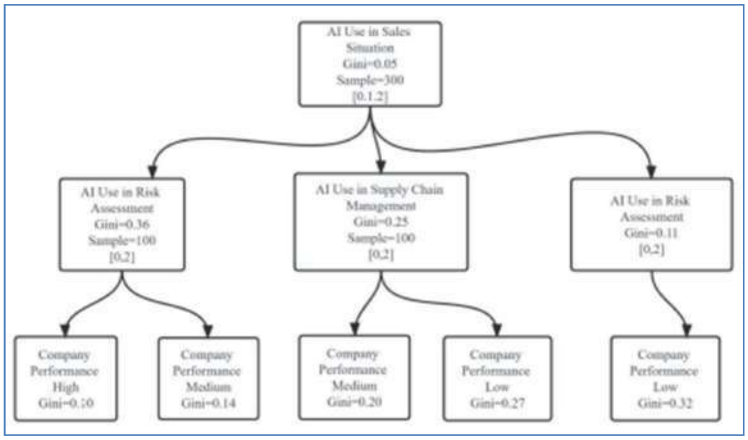

Fig. 1 Decision tree model of business decision making.

In this study, cross-validation assessed the decision tree model's predictive performance. On the training set, the model achieved an accuracy of 0.87, a recall rate of 0.86, and an F1 score of 0.865. For the test set, the accuracy was 0.85, recall was 0.84, and the F1 score was 0.83 (see Table 5). Although the model performed slightly better on the training set compared to the test set, the results indicate strong generalization ability. This highlights the significance of effective feature selection, model tuning, and validation strategies. Overall, the decision tree model demonstrates excellent predictive capability regarding AI's impact on corporate decision-making, including sales, risk assessment, and supply chain management.

Table 5 Decision tree model performance

Indicators	Training Set	Test Set
Precision	**87%**	**85%**
Recall	**86%**	**84%**
F1 score	**0.865**	**0.83**

This study's findings confirm that AI tools positively influence business decision-making. It also highlights variations in AI application across different types of enterprises, offering valuable insights for companies selecting and using AI tools. Using a decision tree model, the study predicts the impact of AI applications on business decision-making and identifies four specific scenarios:

- High AI Use in Risk Assessment and Sales Situations: High company performance
- Low AI Use in Risk Assessment and High AI Use in Sales Situations: Medium company performance
- High AI Use in Supply Chain Management and Medium AI Use in Sales Situations: Medium company performance
- Low AI Use in Supply Chain Management and Medium AI Use in Sales Situations: Low company performance.

4. Conclusion

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This study provides comprehensive insights into how machine learning influences business decision-making through a methodologically rigorous approach. Data was collected through online surveys involving over 500 companies, in-depth interviews with 15 industry leaders, and social media analysis using advanced text mining techniques. Data preprocessing involved cleansing, transformation, integration, feature selection, and discretization to ensure high-quality analysis. The study applied multiple linear regression to quantify the impact of AI input, enterprise size, and the number of AI projects on business performance, yielding a predictive equation that reflects these factors' influence. K-means clustering categorized enterprises into three distinct groups: Start-ups, Mid-Sized Tech Businesses, and Large Industry Leaders, based on their AI usage, performance metrics, and project volume. Additionally, a decision tree model, developed using the C4.5 algorithm and validated through cross-validation, demonstrated robust predictive performance with high accuracy, recall, and F1 scores. The model identified key scenarios where AI usage impacts business performance, providing actionable insights for optimizing AI strategies. These findings are consistent with existing literature and underline the positive role of AI in enhancing strategic decision-making across various enterprise types.

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