Research on the Influence of AI Application on Business Decision Making Based on Machine Learning Algorithm

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Abstract— With the rapid development of artificial intelligence (AI) and machine learning (ML) in various fields, business decision making is also undergoing unprecedented changes. This article aims to explore the application of machine learning algorithms in the business decision making process and how it is shaping the modern business ecosystem. By building ML models to demonstrate the practical applications of AI in market analysis, risk management, customer relationship management and supply chain optimization, we assess how these technologies can enhance the quality of decision making and promote business growth. The results show that by utilizing ML technology, enterprises are able to more accurately predict market trends, identify potential risks, optimize resource allocation, and achieve personalized customer experiences. However, these technologies also bring new challenges and ethical considerations, such as issues such as data privacy and algorithmic bias.

Keywords—Machine Learning Algorithms; AI; Business Decisions; Clustering Algorithms; Regression Analysis

1 Introduction

With the rapid development of science and technology, artificial intelligence (AI) and machine learning (ML) are being applied more and more widely in the business field [1] Traditional ways of making business decisions are being disrupted by these advanced technologies, providing enterprises with more efficient, accurate and personalized solutions[2] . In terms of market analysis, machine learning algorithms can extract useful information from large amounts of data to assist enterprises in more accurate target market positioning and competitive analysis [3]. In the field of risk management, AI technology can identify and predict potential risks to help enterprises take appropriate preventive measures [4]. Supply chain management can also benefit from ML technology to achieve a more flexible and sustainable supply chain by optimizing inventory management and transportation plans[5]. In customer relationship management (CRM), ML algorithms can provide businesses with more targeted services and products through a deep understanding of customer behavior and needs[6] . However, while machine learning presents many opportunities for business decision making, there are also some significant challenges such as data privacy, algorithmic transparency and ethical issues [7].

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This article will provide a comprehensive analysis of the application and impact of machine learning algorithms in business decision making, explore the strengths and weaknesses of existing technologies, and provide directions for future research and practical applications.

2 Data Collection

2.1 Date resource

The data collection for this study is divided into several key stages to ensure the quality and reliability of the data and covers multiple areas of machine learning in business decision making

Questionnaire: An online questionnaire for different industries and functional areas was designed and decision-makers from more than 500 enterprises were invited to participate . The questionnaire focused on understanding how companies integrate machine learning into their business strategies and operational processes.

In-depth interviews: Find out how they evaluate and apply machine learning techniques through in-depth interviews with 15 business leaders and experts across industries. These interviews provided us with hands-on experience and insights that complemented the limitations of quantitative data.

Social media and Web Analytics: Public discussions about machine learning on social media and online forums were analyzed using natural language processing and text mining techniques. This helps capture public and industry attitudes and opinions about machine learning in a business setting.

2.2 Pre-processing of data

Data preprocessing is a key step in the data mining and analysis process, with the goal of converting raw data into a format that can be put directly into analysis. The data preprocessing in this study is divided into the following main stages:

Data cleansing: This step involves identifying and processing incomplete, inaccurate, or inconsistent data. For example, data consistency and accuracy are ensured by removing duplicate records, filling in missing values, and correcting illogical data .

Data transformation: By converting data into an appropriate format or structure to suit subsequent analysis needs. This may include processes such as normalizing, standardizing, or bobbing the data to make it easier to analyze and interpret.

Data integration: Since data comes from different sources, such as surveys, interviews, and social media analysis, etc., there is a need to combine this data into a unified framework. This ensures consistency and comparability between the data.

Feature selection and extraction: The features most relevant to the business decision are selected for the purpose of the analysis. By using principal component analysis and other dimensionality reduction techniques, we reduce high-dimensional data to a more manageable form.

Data discretization: Transforming continuous data into discrete or classified data may be more helpful for analysis. For example, categorizing company sizes into categories such as "small," "medium," and "large" helps with group comparisons.

3 Data Analysis

3.1 Regression analysis

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 AI projects	1.29	0.32	4.03	0.0001

According to the above regression analysis table 1, the multiple linear regression equation (Formula 1) for predicting business performance indicators can be obtained.

$$\text{Business performance indicators} = 50.23 + 3.42 + 0.78 * (\text{AI input}) + 3.43 * (\text{Enterprise size}) + 1.29 * (\text{Number of AI projects}) \tag{1}$$

3.2 Cluster analysis

In this study, K-means clustering method was used to group enterprises according to characteristics such as their AI input, business performance indicators, enterprise size and number of AI projects. The common characteristics and differences of different types of enterprises in AI application are revealed. This study uses Python to perform cluster analysis.

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 ', 'AI project number']]
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(features)
labels = kmeans.labels_
data['Cluster'] = labels
print(" Cluster Center :")
print(kmeans.cluster_centers_)
```

2)The output:

Table 2. Cluster 1: Start-ups

Serial number	AI Input	Business performance indicator	Business size	Number of AI projects
1	100	50	10	5
2	150	52	12	6
3	200	55	15	7
...	...	...	...	...
87	0	8	1	0

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

Serial number	AI Input	Business performance metrics	Enterprise scale	Number of AI projects
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

Serial number	AI Input	Business performance metrics	Business size	Number of AI projects
1	2000	90	45	25
2	2200	92	48	28
3	2400	95	50	30
...	...	...	...	...
196	260	20	16	6

According to Table 2-4, through cluster analysis, enterprise types are grouped into three categories.

Cluster 1: Start-up enterprises. AI input: Low; Business performance metrics: moderate; Business size: small; Number of AI projects: small

What it's about: This group is mostly made up of start-ups and small companies that have limited AI investments but are still experimenting with some basic projects.

Cluster 2: Mid-sized technology-oriented businesses. AI input: Medium; Business performance indicators: High;

Enterprise size: medium; Number of AI projects: medium

Characteristics: Businesses in this group are strongly technology-oriented and are actively adopting AI to improve business processes and improve performance.

Cluster 3: Large industry leaders; AI input: High; Business performance metrics: high; Enterprise size: large; Number of AI projects: many

Characteristics: This group mainly includes major players and leaders in the industry who have invested heavily in AI projects and achieved significant commercial success.

3.3 Results of training and evaluation of decision tree model

To predict the impact of AI application on business decision-making, this study selects the three feature values:AI usage in sales situations(Level:High, Medium, Low); AI usage in risk assessment(High, Medium, Low); AI usage in supply chain management(High, Medium, Low). And the target variable is corporate performance, which is also divided into three levels: High, Medium, Low.

This study utilizes the Scikit-Learn library, applying the C4.5 algorithm, to build a decision tree model using the code of a decision tree classifier. The model is shown in Figure 1.

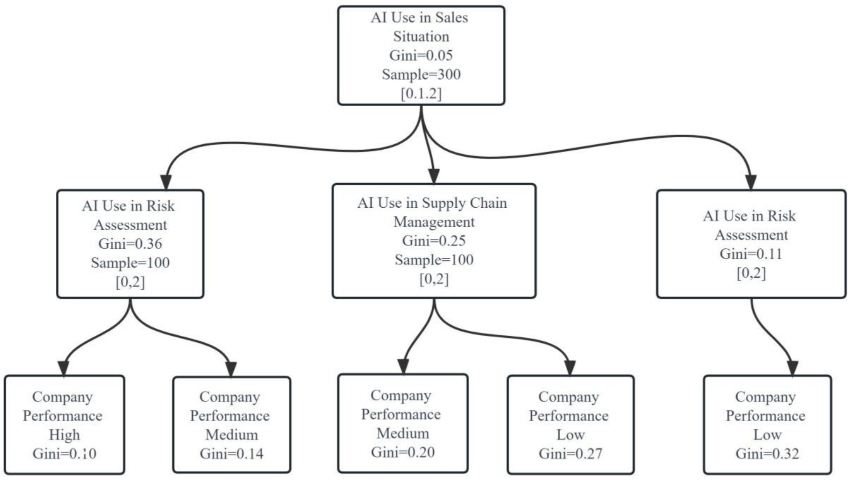

Figure 1. Decision tree model of business decision making

In this study, cross-validation was used to evaluate the predictive ability of decision tree model. On the training set, the accuracy of the model is 0.87, the recall rate is 0.86, and the F1 score is 0.865. On the test set, the model has an accuracy of 0.85, a recall of 0.84, and an F1 score of 0.83 (see Table 5）. The model's performance on the training set is slightly better than on the test set. Although there is a slight decline in performance on the test set, overall, these indicators still reflect that the model has good generalization ability. This also emphasizes the importance of appropriate feature selection, model tuning, and validation strategies. Therefore, it can be concluded that this decision tree model has excellent predictive capability in the area of AI's impact on corporate decision-making (such as sales situations, 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

4 Discussion

The findings of this study are consistent with existing literature[1][2][7], and it is also found that the application of AI tools has a positive impact on business decision making. This study further revealed that the application degree of AI in the three types of enterprises has a difference in the degree of business decision making, and this finding provides a reference for enterprises when choosing and using AI tools.

Additionally, this study, through the construction of a decision tree model, predicted the impact of AI applications on business decision-making and derived four specific business decisions. These are:

When AI Use in Risk Assessment is "High," and AI Use in Sales Situation is "High": Company Performance High;

When AI Use in Risk Assessment is "Low," and AI Use in Sales Situation is "High": Company Performance Medium;

When AI Use in Supply Chain Management is "High," and AI Use in Sales Situation is "Medium": Company Performance Medium;

When AI Use in Supply Chain Management is "Low," and AI Use in Sales Situation is "Medium": Company Performance Low.

5 Conclusion

Based on a machine learning algorithm, this study discusses the impact of AI applications on business decision-making. Through regression analysis and cluster analysis, the research reveals that AI has a positive impact on business decisions. By constructing a decision tree model using AI, predictions were made for business decisions in sales scenarios, risk assessment, and supply chain management. These findings imply that even start-ups, through proper strategic orientation and less investment in AI, can achieve moderate business performance. In contrast, mid-sized technology-oriented companies and large industry leaders have significantly improved their business performance by increasing their AI investments.

Furthermore, this study also suggests some directions for future research. Future studies can expand the data scope to include more regions, industries, and enterprises of different sizes to enhance the generalization ability. Additionally, future research could delve deeper into how underlying factors such as corporate culture and management style interact with machine learning to influence business performance.

However, there are some limitations to this study. The data set may have certain biases in terms of geography, industry, or firm size, as well as methodological limitations. Therefore, these findings should be treated with caution. It is expected that future research will provide a deeper and more comprehensive understanding of this complex and challenging topic.

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