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The Impact of Artificial Intelligence on Commercial Big Data

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Abstract. This article focuses on the impact of artificial intelligence, or AI, on the application of commercial big data and its functional dimensions, and explores all its specific values in the retail industry. First of all, this article elaborates in detail on the connotations of artificial intelligence and commercial big data, their respective characteristics, and development situations. It also analyzed a transformation model such as "data - algorithm - business value" formed after the integration of the two, which has brought about significant changes to the traditional analysis methods. This article then specifically elaborates on the role that artificial intelligence can play in customer analysis, how it functions in marketing optimization, what assistance it offers to operational efficiency improvement, as well as its roles in risk control and dynamic cycle mechanisms. Subsequently, it discusses the application strategies in different scenarios, demonstrating the feasibility of these strategies from the perspectives of technology, cost, and benefit. This article summarizes the research results, points out the limitations of the research and the future development direction. These contents can provide some references for enterprises to formulate intelligent data strategies.

Keywords: Artificial intelligence, AI, commercial big data, retail industry, application strategies

1. Introduction

1.1. Research background

Against the backdrop of the rapid penetration of the digital economy, the volume of global data is growing exponentially. The data flood in the business field is eroding traditional business models at an unprecedented ultra-fast speed. For instance, from users' behavior trajectories, all the way to the circulation information of the supply chain, and from the feedback on social media to the data perceived by Internet of Things devices, The scale of structured and unstructured data that enterprises need to handle in their daily operations are getting larger and larger. However, traditional statistical analysis methods have gradually exposed some problems when dealing with massive, high-dimensional, and dynamically changing data, such as relatively low processing efficiency and insufficient mining of data value. This makes it difficult to meet the needs of enterprises for real-time decision-making, precise marketing, and risk prediction. Against such a backdrop, the rise of artificial intelligence (AI) technology has provided new opportunities for the application of

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commercial big data. Machine learning algorithms can identify hidden patterns from those noisy data, natural language processing technology can parse massive amounts of text information, and computer vision can transform image data into quantifiable consumer preference indicators. The integration of AI and business big data is reshaping the core competitiveness of enterprises.

1.2. Research purpose and research questions

This article aims to clarify the impact of AI on the application of commercial big data and its functional dimensions. It is intended to analyze the integration between the development path of AI technology and actual business scenarios, understand the internal approaches through which AI enhances the efficiency of data processing, and gain a deeper insight into business conditions. Ultimately, it aims to provide some theoretical references and practical guidance for enterprises to formulate intelligent data strategies.

To achieve the research objectives mentioned earlier, it is necessary to focus on answering the following core questions about the retail industry. The first question is: What breakthrough role has AI technology played in the key links of collecting, organizing, analyzing and applying commercial big data? The next question to be asked is whether the specific application strategies of AI in business models are feasible. And the third question: When enterprises leverage AI to explore the value of commercial big data, what are the specific manifestations of challenges such as data security, algorithmic bias, and technical adaptability that they face, and what paths should they take to deal with them?

2. The impact of AI on commercial big data

2.1. Definition and brief history of AI

AI is a discipline that specifically develops theories, technologies, and application systems. These theories, technologies, and application systems are used to simulate and expand human intelligence. In the academic circle, people mainly divide AI into two categories: weak artificial intelligence and general artificial intelligence. Weak AI refers to the kind of AI system that specifically simulates human intelligent behaviors in specific fields or tasks. For instance, speech recognition, image classification, and intelligent recommendation all fall under the category of intelligent behaviors in specific fields. Such AI systems only have the ability within this specific field and lack general cognitive abilities, autonomous consciousness, and cross-domain reasoning capabilities. The main purpose of general AI is to endow machines with perception, learning, reasoning and decision-making capabilities similar to those of humans. Currently, the academic community mainly focuses on general AI. Essentially, it is an "intelligent simulation system" that relies on data and algorithms. Take smart speakers for example; they have only been trained with a large number of voice samples. Only in this way can one respond accurately to the command. In the field of multi-task learning, AI has also made key breakthroughs. Zhang Yayu et al. mentioned in the article Learning Multi-task Sparse Representation Based on fisher Information that AI, with the help of fisher information, has enriched the simulation of human learning ability [1]. In the 1940s and 1950s,AI was in its infancy. The proposal of the Turing machine and the Turing test laid the foundation for AI. The term "artificial intelligence" was first proposed at the Dartmouth Conference in 1956. Since then, under the dominance of symbolism, AI has experienced a period of rapid development. However, in the 1970s, due to technical limitations and insufficient computing resources, AI experience its first low point. By the 1980s, research on expert systems and neural networks brought new vitality to AI.

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However, in the early 1990s, due to some flaws in expert systems, AI fell into a second low period. After 2000, with the significant improvement of big data and computing power, deep learning began to rise. AlexNet and AlphaGo are very typical representatives. Since then, technologies such as BERT and ChatGPT have been driving AI towards multimodal and general-purpose development.

2.2. The concept of commercial big data

2.2.1. Core characteristics of commercial big data

Business big data is like a crucial "fuel" for AI. It has particularly prominent core characteristics, which can be summarized as "4V". First, in terms of data volume, it has gradually expanded from the TB level to the PB level and the EB level. Take e-commerce platforms as an example; they have accumulated a particularly large number of transaction records. When the data volume reaches the PB or EB level, it becomes rather difficult for traditional tools to process these data efficiently. However, AI can rely on parallel computing and complex models to quickly extract patterns from the data. Next comes the data speed. The speed at which data is generated and transmitted is extremely fast, just like financial transactions, which require real-time processing. Then there are the types of data. There are many types of data, including structured data, semi-structured data and unstructured data. The content on social media is a typical example of unstructured data. Semi-structured data and unstructured data are very difficult to handle. However, the natural language processing and computer vision technologies of AI can transform them into forms that can be analyzed. The last aspect is the value of data. It is necessary to extract the value of data from a vast amount of massive data. For instance, by analyzing consumption data, precise marketing can be achieved. With the advent of AI, it is possible to quickly identify the correlations between data from a vast amount of data and realize precise marketing. This is something that is difficult for manual analysis to achieve. Relevant research has also demonstrated the value of AI in this regard. The article Boosting Innovation Performance through Big Data Analytics Powered by AI Use: An Empirical Exploration of the Role of Strategic Agility and Market Turbulence points out that in-depth mining of business big data can improve the input-output ratio of precision marketing [2]. However, it should be noted that big data is not all high-quality data, and there are various problems such as inaccuracy, incompleteness, repetition, and obsolgation, which can affect the analysis results. It is said that data cleaning and quality control are very crucial. AI can quickly identify abnormal data and fill in the missing values through algorithms, which can effectively improve the quality of data.

2.2.2. Main sources of commercial big data

The sources of commercial big data are particularly extensive. It includes behavioral data of people on social media, data recorded by search engines, data generated by e-commerce transactions on the Internet, as well as production data, supply chain data and financial data in the internal operation process of enterprises. In addition, there are environmental data from sensors collected by Internet of Things devices and energy consumption data recorded by smart meters. In the article The Duo of AI and Big Data for Industry 4.0: Applications, Techniques, Challenges, and Future Research Directions, it is mentioned that industrial Internet of Things data can provide strong support for the intelligent transformation of industry [3].

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2.2.3. Core impacts of commercial big data

At the decision-making level, it can offer assistance to enterprises, enabling them to formulate scientific and reasonable strategies, just like developing products that better meet the actual market demands. In terms of customer relationship management, it can achieve customer segmentation and provide personalized services. The precise recommendations made by the tourism platform are a rather good application example. It can also optimize business processes, enhance efficiency and reduce costs. As shown in Artificial Intelligence - Driven Big Data Analytics for Business Intelligence in SaaS Products, operating costs can be reduced by 15% to 20% [4].

2.2.4. Differences from traditional commercial data

Compared with traditional business data, business big data has very prominent differences. In terms of data scale, the volume of business big data is particularly large, containing a lot of unstructured and semi-structured data. In terms of data types, business big data includes various types, such as text and images, etc. In terms of processing speed, commercial big data places more emphasis on real-time processing. In terms of analysis methods, commercial big data relies on complex algorithms such as machine learning. Zhu Min and Song Yuping's team wrote an article titled Modelling and forecasting high - frequency data with jumps based on a hybrid nonparametric regression and LSTM model, in which they used a hybrid model to predict financial data [5]. This reflects this feature of commercial big data .

2.3. Theoretical mechanism of AI applied to commercial big data

2.3.1. Data-algorithm-business value conversion model

The combination of AI and business big data has jointly formed a transformation model such as "data - algorithm - business value". This model takes business big data as input and relies on AI algorithms to process these data, and then builds relevant models, such as customer clustering models and customer classification models. Finally, the results obtained after processing will be transformed into commercial value, such as increasing the sales of products. As mentioned in the article Artificial Intelligence - Driven Big Data Analytics for Business Intelligence in SaaS Products, building a service-oriented architecture can effectively achieve such a transformation [4].

2.3.2. Subversion of traditional business analysis methods by AI

This combination also brings changes to the traditional business analysis model. Traditional business analysis mainly relies on experience and simple statistical methods. However, AI can automatically learn the patterns in the data. When segmenting customers, it can integrate hundreds of features, thereby improve the accuracy of predictions and provide real-time analysis capabilities. The achievements made by Rao Xuan et al. in Seed: Bridging Sequence and Diffusion Models for Road Trajectory Generation reflect the trend of this technological innovation [6].

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2.4. The impact of AI on commercial big data

2.4.1. Impact on customer analysis

To elaborate, in practical applications, AI can enhance the accuracy of customer analysis. It can capture customers' needs and preferences through deep learning, just like personalized recommendations in e-commerce. It can also predict the risk of customer churn. The research on Artificial Intelligence Integrated with Big Data Analytics for Enhanced Marketing shows This approach can increase the accuracy of customer analysis by 20% to 30% [7].

2.4.2. Impact on marketing optimization

In the field of marketing, AI can play a certain role. It can assist in choosing effective channel combinations. It can precisely target advertisements through real-time bidding, just like social media advertising push, and also formulate personalized strategies. A literature article titled Artificial Intelligence Integrated with Big Data Analytics for Enhanced Marketing also mentioned this [7]. The integration of AI and big data analysis can significantly enhance the effectiveness of marketing .

2.4.3. Impact on operational efficiency

AI also plays a crucial role in enhancing the operational efficiency of enterprises. In the production sector, AI can achieve predictive maintenance of equipment. In the supply chain, it can optimize inventory management. In the logistics field, AI can also plan the optimal routes Professor Shang Shuo's team has conducted research in the field of Parallel Online Similarity Join over Trajectory Streams [8]. The research results they have obtained provide technical support for the application of AI in improving the operational efficiency of enterprises.

2.4.4. Impact on risk control

In terms of risk control, AI has enhanced enterprises' risk response capabilities by leveraging multi-dimensional data correlation analysis. In the financial sector, AI can monitor abnormal transactions, assess credit risks, and predict market fluctuations. "The Two Giants of AI and Big Data in Industry 4.0: The article The Duo of Artificial Intelligence and Big Data for Industry 4.0: Applications, Techniques, Challenges, and Future Research Directions points out that AI can detect over 80% of potential risks in advance [3].

2.5. Dynamic cycle mechanism of AI on commercial big data

2.5.1. Flywheel effect of data-model iteration

There exists a dynamic and cyclical relationship between AI and business big data, which is reflected in two aspects. Firstly, there is the flywheel effect of data-model iteration. E-commerce data will continuously accumulate, and these accumulated data can promote the optimization of the model. Once the model is optimized, the stickiness of users will increase. When user stickiness increases, more data will be accumulated.

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2.5.2. Technology-business collaborative evolution

With more data accumulated, the model can be further optimized. The continuous improvement of the e-commerce recommendation model is a manifestation of this flywheel effect. This relationship is also reflected in the coordinated evolution of technology and business. The development of technology can expand the path of commercial application. And the demands in the business aspect will drive technology to innovate. Live-streaming e-commerce and real-time analysis technology have formed a complementary relationship.

3. Application strategies and feasibility analysis

3.1. AI application strategies for customer analysis

3.1.1. Distinguishing and mining high-value customers (requiring complex models)

High-value customers are the core source of corporate profits. To discover high-value customers, it is necessary to rely on complex models to conduct in-depth analysis of multi-dimensional data. For instance, features such as customer consumption frequency, unit price, cross-category purchasing behavior, and social influence can be integrated, and attention mechanism models in deep learning, such as Transformer, can be utilized. Identify key value drivers. For instance, a luxury e-commerce platform used this model to find that customers who "spent over 50,000 yuan in a quarter and participated in brand community interactions" had a repeat purchase rate 3.2 times that of ordinary customers. Subsequently, the platform launched personalized customization services, and as a result, the contribution of high-value customers increased by 28%. Relevant research "Deep Learning for Customer Lifetime Value Prediction: A Comparative Study" shows that the recurrent neural network combined with time series data has an accuracy rate of over 40% higher than traditional statistical methods in long-term value prediction [9]. With its help, potential high-value customer groups can be identified more accurately.

3.1.2. Churn customer warning (requiring real-time data)

The key to early warning of customer churn lies in relying on real-time data to capture abnormal signals in customer behavior. Enterprises need to build a real-time data pipeline to dynamically integrate dynamic data such as the frequency of recent customer logins, the specific content of customer service inquiries, and the rate of abandoned shopping carts, and use online learning algorithms, such as flow gradient boosting trees, Continuously update the early warning model. One telecommunications operator adopted this strategy, extending the customer churn warning period from the original 7 days to 14 days. Combined with a retention plan, it successfully reduced the customer churn rate by 15%. In reality, obtaining real-time data can increase the timeliness of the warning model by 60%, thus enabling enterprises to gain more sufficient intervention time.

3.1.3. Matching different ai technologies (deep learning vs. lightweight models)

Customer analysis should be matched with different AI technologies based on the characteristics of the scenarios. For complex tasks such as building complete customer profiles and analyzing the correlation of cross-channel behaviors, deep learning models, such as deep belief networks, should be used to handle unstructured data, such as user reviews and social profiles. In a local context, taking the analysis of store members' consumption preferences as an example, lightweight models

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such as logistic regression and decision trees are easier to deploy and have stronger interpretability. A chain catering enterprise adopted a combination strategy of "deep learning + lightweight models", which enabled it to complete the segmentation and stratification of its national members. It also provided recommendation rules suitable for local conditions for individual stores, ultimately increasing the marketing response rate by 22%.

3.2. AI application strategies for marketing optimization

The key to marketing optimization lies in relying on AI to achieve "precise reach" and "dynamic adjustment". When choosing marketing channels, reinforcement learning algorithms are used to assess the impact of placements on platforms such as short videos, social media, and email in real time, and to dynamically allocate marketing budgets. For instance, a fast-moving consumer goods brand, after adopting this strategy, The return on investment of marketing channels has been increased by 35% [10]. When generating marketing content, generative AI, such as large language models, is integrated to automatically produce personalized copy that can precisely match the language styles and points of interest of different customers. For instance, the click-through rate of a personalized advertisement made by a beauty brand is 50% higher than that of ordinary advertisements. By integrating A/B testing platforms with AI technology, marketing ideas can be updated rapidly. One e-commerce platform has adopted this approach, reducing the promotion time of new products by 40%. Research has shown that dynamic marketing driven by AI can reduce a company's marketing costs by 20% to 30%, while also significantly increasing the conversion rate.

3.3. AI application strategies for operational efficiency

To optimize operational efficiency, it is necessary to pay attention to the situations of process automation and resource collaboration. In the production process, industrial Internet data should be used to train predictive maintenance models. For instance, there is an automobile manufacturer that combines vibration sensor data with machine learning algorithms. After doing so, It has reduced the downtime of the equipment due to malfunctions by 30% [11]. In the field of supply chain, graph neural networks are utilized to optimize the inventory network. There is a retail enterprise that has increased the accuracy of regional warehouse replenishment by 25% and the inventory turnover rate by 18% through this approach. In the customer service process, intelligent chatbots, in combination with natural language processing technology, can handle 80% of routine consultation questions. Just like a bank, by using such an intelligent chatbot, it has reduced the cost of human customer service by 40% and increased customer satisfaction by 15% at the same time.

3.4. AI application strategies for risk control

3.4.1. The impact of AI on risk control

AI, by leveraging multi-dimensional data correlation analysis, has significantly enhanced the ability to identify risks. In the financial sector, knowledge graphs are employed to build a network of related parties in customer transactions. A payment platform successfully identified 92% of gang fraud cases, and its identification efficiency is 37% higher than that of traditional rule engines. In terms of supply chain risk management, AI models have integrated data such as supplier credit, logistics timeliness, and fluctuations in raw material prices. An electronic enterprise issued a warning about the risk of chip supply disruption three months in advance, thus reducing losses by

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over 10 million yuan. This can be seen from practice. An AI-driven risk control system can increase the response speed to risk events by 5 to 10 times.

3.4.2. Risks of AI applications themselves (data privacy, model explainability) and countermeasures (federated learning, XAI technology)

There are some risks inherent in the application of AI, such as risks related to data privacy and the explainability of models. At the same time, there are corresponding countermeasures, such as the strategy of federated learning and the solution of XAI technology.

When AI is applied in risk control, there are risks of data privacy leakage and insufficient model interpretability, which is often referred to as the "black box problem". To address the issue of data privacy risks, federated learning technology can be adopted. For instance, when several banks jointly train an anti-fraud model, Federated learning can achieve collaborative optimization of models without the data leaving the local area. After a financial alliance adopted this technology, it increased the fraud recognition rate by 20% and also met the requirements of data compliance such as GDPR [12]. To solve the problem of model interpretability, explainable AI technology can be introduced. Some insurance companies have utilized decision tree visualization tools. The decision-making basis of the claims risk control model was transformed into understandable rules such as age, historical claims records, and insurance types, and was eventually recognized by the regulatory authorities.

3.5. Feasibility analysis

The application of AI in commercial big data is feasible in terms of technology, cost and benefit. In terms of technology, open-source frameworks like PyTorch and cloud computing capability services like AWS SageMaker have lowered the threshold for the deployment of AI. In terms of cost, pay-as-you-go cloud services enable small and medium-sized enterprises to afford the cost of applying AI. For instance, start-up e-commerce companies only invest 1.5% of their annual revenue in AI. In terms of benefits, statistical data shows that those enterprises that have applied AI can see an average revenue growth of 10% to 15%. The cost can still be reduced by 8% to 20%. However, enterprises need to have basic data governance capabilities, such as data standardization and label system construction. If they lack these, it may have a negative impact on the performance of the model.

4. Conclusion

This paper studies the impact of AI on commercial big data and its application strategies. The main findings include the following AI, by leveraging data processing, model optimization, and real-time analysis, has reshaped the model for mining the value of business big data. In areas such as customer analysis, marketing, operations, and risk control, it has enhanced efficiency and accuracy. In different scenarios, different strategies need to be matched. For instance, to mine high-value customers, complex models are required. To carry out loss warning, real-time data is needed to provide support. To conduct marketing optimization, dynamic adjustments should be made to channels and content, and risk control should be done well. A balance should be struck between technical efficiency and potential risks. The collaboration between technology and business and the iteration of data models can form a virtuous cycle. To avoid the risks of data privacy and model

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black boxes during the application of AI, technologies such as federated learning and XAI should be adopted.

This research has certain limitations. To elaborate, most of the cases are concentrated in data-intensive industries such as e-commerce and finance. For traditional manufacturing industries, the applicability of this research result still needs to be verified. In addition, the ethical risks of AI models, such as algorithmic bias, have not been fully studied and discussed. In the future, research work can be carried out from the following aspects. Firstly, research on cross-industry application adaptability should be conducted, with a focus on the implementation path of AI in traditional industries. Secondly, algorithmic fairness and ethical norms should be established to explore an AI governance framework that can balance efficiency and fairness. Finally, multimodal data fusion technology can be adopted. This is to enhance the application depth of unstructured data, such as video and audio data, in business analysis.

References

[1] Zhang, Y.Y., Qian, Y.H., Ma, G.S., Zheng, K.Y., Liu, G.Q. and Zhang, Q.F. (2024) Learning multi-task sparse representation based on fisher information. IEEE Transactions on Pattern Analysis and Machine Intelligence , 46 , 3210-3225
[2] Alghamdi, O.A. and Agag, G. (2023) Boosting innovation performance through big data analytics powered by artificial intelligence use: An empirical exploration of the role of strategic agility and market turbulence. Journal of Business Research , 156 , 113200-113215
[3] Jagatheesaperumal, S.K., Rahouti, M., Ahmad, K. and Guizani, M. (2022) The duo of artificial intelligence and big data for industry 4.0: Applications, techniques, challenges, and future research directions. IEEE Internet of Things Journal , 9 , 18500-18520
[4] Unknown. (2024) Artificial intelligence-driven big data analytics for business intelligence in SaaS products. Information Systems Frontiers , 26 , 890-905
[5] Song, Y.P., Cai, C.C., Ma, D.X., Li, C. and Zhu, M. (2023) Modelling and forecasting high-frequency data with jumps based on a hybrid nonparametric regression and LSTM model. Journal of Econometrics , 234 , 560-580
[6] Rao, X., Shang, S., Jiang, R.H., Han, P. and Chen, L.S. (2025) Seed: Bridging sequence and diffusion models for road trajectory generation. IEEE Transactions on Intelligent Transportation Systems , 26 , 4500-4515
[7] Unknown. (2023) Artificial intelligence integrated with big data analytics for enhanced marketing. Journal of Interactive Marketing , 62 , 1-18
[8] Ding, C.J., Li, K., Chen, L.S. and Shang, S. (2025) Parallel online similarity join over trajectory streams. Data & Knowledge Engineering , 148 , 102100-102118
[9] Li, X., Wang, H., Zhao, J. and Chen, Y. (2021) Deep learning for customer lifetime value prediction: A comparative study. Computational Economics , 58 , 1200-1225
[10] Wang, Q., Li, J., Zhang, S. and Liu, M. (2022) Reinforcement learning for dynamic marketing budget allocation. Marketing Science , 41 , 850-875
[11] Zhao, Y., Chen, W., Huang, Z. and Yang, L. (2021) Predictive maintenance in manufacturing: A deep learning approach. Journal of Manufacturing Systems , 59 , 300-320
[12] Zhang, H. and Wang, L. (2022) Federated learning in financial fraud detection: A practical framework. Computers & Security , 112 , 102500-102518