RESEARCH ARTICLE

Agricultural product brand image and brand strategy based on artificial intelligence

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The branding of agricultural products is an important means to enhance the competitiveness of agricultural industry and promote the modernization of agriculture. However, at present, there are still many problems in China's agricultural product branding such as insufficient brand influence, fuzzy brand image, and insufficiently in-depth excavation of brand value. This study applied graph neural network (GNN) model to characterize the data related to agricultural products and get the embedding vectors of users and agricultural products. The effectiveness and superiority of the model were verified through comparison experiments and conversion rate tests. Compared to traditional questionnaires, the deep-learning model constructed a more personalized brand image, which better reflected user and product characteristics, meeting user preferences and expectations, and improved brand image scores, demonstrating the model's effectiveness and superiority. The brand image constructed by proposed model could better attract users' attention and interest, promote users' clicking and purchasing behavior, and improve the conversion rate of the brand image, while the brand image constructed by the traditional method was relatively low, indicating that the brand image constructed by proposed model could better improve the market competitiveness of agricultural products and economic benefits.

Keywords: agricultural products; artificial intelligence; brand image; branding; strategy.

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Introduction

The tide of informatization and intellectualization is sweeping across all fields at an amazing speed, injecting new vitality into the transformation and upgrading of various industries. Agriculture, as the foundation of human survival and development, is facing unprecedented opportunities and challenges. As a kind of disruptive innovation, artificial intelligence (AI) technology plays an increasingly important role in agricultural production process, which not only improves agricultural production efficiency and product quality, but also shows great potential in brand image building and brand strategy innovation of agricultural products [1-4]. As a big agricultural country, China has abundant agricultural resources and huge market. Brand building of agricultural products is an important means to enhance the overall competitiveness of China's agriculture and promote agricultural modernization [5]. However, there are still some problems such as the lack of brand influence and the fuzzy brand image, which seriously restrict the market share and consumer satisfaction of agricultural products in China. In addition, the number of applications for similar trademarks is also increasing due to fierce competition in the market and the motivation of some applicants to “go near famous brands,” especially in some popular industries or around famous brands [6, 7].

Under the background of accelerating the process of agricultural modernization and informatization, the research on agricultural product brand image and brand strategy based on artificial intelligence technology has been widely concerned by academic and practical circles [8, 9]. This paper aimed to explore the status quo, theoretical basis, and practical path of AI in the application of agricultural products branding [10-12]. By integrating AI technologies such as machine learning and data analytics, this study planned to enhance the precision of market segmentation and consumer profiling. Using these tools, businesses could gain deeper insights into consumer behavior, preferences, and expectations, thereby crafting more effective branding strategies [13, 14]. Moreover, the application of AI could optimize the entire branding process from initial concept to market execution by providing actionable insights and predictive analytics, which not only accelerated the development of a robust brand identity but also ensured that the brand resonates with its target audience, thereby increasing market penetration and consumer loyalty. Additionally, the use of AI-driven models for managing the branding lifecycle promised to elevate the competitive edge of Chinese agricultural products, aligning them more closely with evolving market demands and consumer trends [15, 16].

Materials and methods

Model for analyzing and processing data

To achieve personalized agricultural product brand image construction, it is first necessary to analyze and process a large amount of data to extract useful information and features. Two types of data were mainly used including agricultural product-related data, covering the type, origin, quality, price, sales volume, and evaluation of agricultural products and user-related data covering users’ basic information, purchase records, feedback, social media dynamics, and so on [17, 18]. These data mainly came from web crawlers, questionnaires, social media platforms, and other channels. To better represent the features of the data, a graph neural network (GNN) model being trained using data related to the brand image of agricultural products was adopted for the feature processing of the data. GCN model was used in this study to take users and agricultural products as nodes in the graph, the association of rules between users and agricultural products as edges in the graph, and attributes of users and agricultural products as features of the nodes. The embedding vectors of users and agricultural products were obtained through the GCN model for the subsequent construction of brand image as follows.

$$H^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\tilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right)$$

The specific structure diagram was shown in Figure 1 [19, 20].

Descriptive indicators of brand image of agricultural products

To measure the level and effect of brand image of agricultural products, a measurement index system of brand image of agricultural products was constructed [21]. At the highest level, the system divided brand image into three main dimensions including brand awareness, brand emotion, and brand association. Each level was further broken down into secondary indicators, providing more specific focus areas. Under brand awareness, secondary metrics included recognition and understanding, which delved into users’ familiarity with brand names, logos, and slogans, as well as their understanding of brand positioning and unique features. Brand sentiment was broken down into preferences and loyalty, examining users’ emotional connection to the brand, including their preferences and likelihood to buy back or

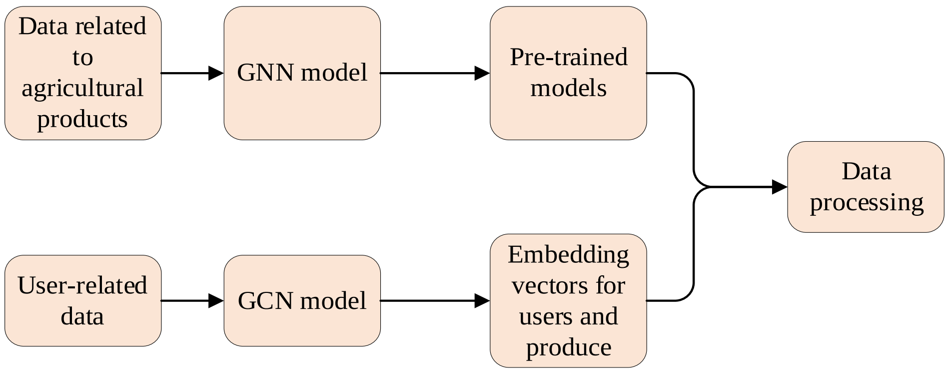

Figure 1. Structure of the model for analyzing and processing data.

recommend the brand to others. Brand associations were divided into relevance and uniqueness, assessing the extent to which users associated brands with other entities and the extent to which they distinguished brands from competitors. This structured approach provided a comprehensive assessment of the brand's presence and impacted in consumers' minds, providing actionable insights for brand managers looking to enhance the image of agricultural brands [22, 23].

Personalized agricultural product brand image construction based on deep learning

The fully connected layer, a core component of deep neural networks, was adopted to map the above obtained embedding vectors of users and agricultural products to the predefined brand image evaluation indexes. The fully connected layer has a powerful nonlinear transformation capability, which can adaptively adjust the weight allocation according to the complex correlation of the input features to realize the effective transformation from the bottom features to the high-level abstract concepts. The formula of the fully connected layer was as follows.

$$y_i = \sigma(Wx_i + b)$$

where y_i was the brand image vector of the i-th user or agricultural product. x_i was the embedding vector of the i-th user or agricultural product. *W* and *b* were the weight matrix and bias vector of the fully connected layer [21, 24]. Through this process, this study realized the intelligent and personalized construction of the brand image of agricultural products based on the user's individualized needs and the characteristics of agricultural products using AI algorithms. Such a construction method not only accurately reflected the brand connotation of agricultural products, but also effectively guided the formulation of brand marketing strategies, promoted the accurate positioning and efficient dissemination of agricultural product brands, and thus enhanced their competitiveness and influence in the market.

Validation of the effect and superiority of proposed model

To verify the practical effect and superiority of the personalized agricultural product brand image construction model based on deep learning technology proposed in this study, a comparison experiment was carefully designed and implemented. "Linshui Chili", a typical representative geographical indication product produced by Linshui County Agricultural Products Development Co., Ltd. (Guang'an, Sichuan, China) was selected as the case object. This company focuses on utilizing local high-quality agricultural resources to develop and promote specialty agricultural products. Due to its unique spicy aroma and local characteristics, the selected product is regarded as the treasure of "the hometown of Chinese pepper" in the industry, and the design and promotion of its e-commerce brand image is crucial [25]. In this study, the e-commerce brand image of the subject product was systematically designed using the deep learning model and compared with the brand image scheme constructed by traditional questionnaire surveys. Twenty entrepreneurs who have made remarkable achievements in the industry and 100 netizens who have extensively participated in online interactions were invited as the evaluation subjects. The e-commerce brand images of the product constructed using the two methods were carefully assessed, respectively [26].

Results

The personalized agricultural product brand image construction model based on deep learning proposed in this study could better reflect the characteristics and needs of users and agricultural products than that of the traditional questionnaire-based method, which constructed a brand image that was more in line with the user's preferences and expectations, and thus improved the scores of the various indicators of brand image and showed the effectiveness and superiority of the proposed model (Table 1).

Table 1. Brand image scoring results under the two methods.

Methodologies	Brand awareness	Brand emotion	Brand association
Proposed model	4.5	4.4	4.3
Traditional method	3.7	3.6	3.5

To verify the influence of the brand image under the two methods on the user's purchasing behavior, the conversion rate of the brand image under the two methods was also tested by simulating the operation of clicking and purchasing on the brand image under the two methods through 100 invited netizens. The clicking and purchasing rates were then recorded [27-29] (Table 2). The results showed that the brand image constructed by the proposed model could better attract users' attention and interest, promote users' click and purchase behavior, and improve the conversion rate of the brand image, while the brand image constructed by the traditional method was relatively low, which indicated that the brand image constructed by the proposed model could better enhance the market competitiveness and economic benefits of agricultural products.

Table 2. Conversion rate of brand image under the two methods.

Methodologies	Click through rate (CTR) (Internet)	Purchase rate
Proposed model	80%	60%
Traditional method	60%	40%

Discussion

In the current era of increasingly fierce competition in the agricultural products market, it is especially crucial to deeply analyze the existing problems in the process of constructing and disseminating the brand image of agricultural products and put forward practical suggestions for improvement. Through the detailed analysis of a large number of agricultural product data, several core challenges have been identified, which include that the current brand image of China's agricultural products generally present the problem of serious homogenization, lack of personalization and differentiation. Many agricultural product brands fail to fully explore their own characteristics and regional cultural connotations, making it difficult for them to adapt to the needs of modern consumers in pursuit of diversified and personalized experiences. To a certain extent, this phenomenon has weakened the market competitiveness of agricultural brands, making them unable to stand out in a wide range of products. In addition, the communication method of agricultural brand image is traditional and single, lacking sufficient innovative elements and interactive means. Traditional marketing channels and modes are often unable to effectively reach most consumer groups, especially the young generation of consumers, which not only limits the proliferation of brand awareness, but also largely affects the consumer's sense of identity and loyalty to the brand. Furthermore, the data support and technical means in the process of agricultural brand image construction are relatively lagging and cannot yet realize accurate positioning and comprehensive assessment [28, 29]. Based on the above issues, the following three targeted recommendations were made by this study.

Suggestion 1: Actively introducing AI technology through deep learning and big data analysis to scientifically build a brand image of agricultural products with personalization and differentiation based on users' consumption habits, preference characteristics, and the quality characteristics and origin advantages of the agricultural products themselves. This strategy aims to enhance consumers' cognitive level of the brand, strengthen emotional resonance, and enrich the brand association space, thereby increasing the brand's market acceptance and willingness to purchase [30, 31].

Suggestion 2: Combining the diversified communication tools such as social networks and short video platforms in the new media environment, utilizing AI algorithms to realize accurate pushing and intelligent recommendation, and innovating the communication ways and means of agricultural brand image.

Suggestion 3: Relying on the data collection and processing capabilities of AI, establishing a perfect brand image database to monitor and analyze brand image-related data in real time including, but not limited to, consumer feedback, changes in market trends, and competitive product dynamics. Through intelligent data analysis, the brand image can be more accurately positioned and adjusted to ensure the scientific and effective brand image design and management. In addition, based on the results of data analysis to continuously optimize the brand image strategy, further enhance the market value and potential premium capacity of agricultural brands, upgrade and transform the agricultural industry, and promote agricultural brands towards the road of high-quality development.

With the theme of "Research on Brand Image and Branding Strategy of Agricultural Products Based on Artificial Intelligence", this study explored how to use deep learning technology to construct and disseminate the brand image of agricultural products in an intelligent and personalized way to enhance the market competitiveness and economic benefits of agricultural products brands. The study proposed a data feature processing method based on graph neural network (GNN) model and a personalized agricultural product brand image construction method based on the fully connected layer model. A measurement index system of agricultural brand image including three core dimensions of brand cognition, brand emotion, and brand association and their sub-indicators were also constructed. The practical effect and superiority of the proposed personalized agricultural brand image construction model based on deep learning were verified through comparative analysis with traditional method and conversion rate tests. The results showed that the brand image constructed by proposed model could better reflect the characteristics and needs of users and agricultural products and was better meeting the preferences and expectations of users, and thus improved the scores of the various indicators of the brand image, which showed the effectiveness and superiority of this proposed model. The brand image constructed by proposed model could also better attract users' attention and interest, promote users' clicking and purchasing behavior, and improve the conversion rate of the brand image, while that of the traditional method was relatively low, indicating that the brand image constructed by proposed model could better improve the market competitiveness of agricultural products and economic benefits.

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References

1. Abdullahi BN, Ma DC, Yeboah FK, Ibrahim HY. 2023. Econometric analysis of China-ECOWAS agricultural products trade. Ciencia Rural. 53(1):16.
2. Ahmed M, Schermel A, Lee JNF, Weippert M, Franco-Arellano B, L'Abbe MR, *et al*. 2022. Development of the food label information program: A comprehensive Canadian branded food composition database. Front Nutr. 8:825050.
3. Arisoy H. 2020. Impact of agricultural supports on competitiveness of agricultural products. Agric Econ-Zemedelska Ekonomika. 66(6):286-295.
4. Bai L, Zhang ZX, Peng X, Gao ZW, Zhao Y, Liang KH. 2023. Application of omics technology in the storage and transportation of agricultural products. Front Sustain Food Syst. 7:13.
5. Cheng JH, Yu PP, Huang YR, Zhang G, Lu CL, Jiang XP. 2022. Application status and prospect of impedance spectroscopy in agricultural product quality detection. Agric Basel. 12(10):1525.
6. Chung K, Park JY, Park K, Kim Y. 2020. Which visual modality is important when judging the naturalness of the agent (artificial versus human intelligence)? Providing recommendations in the symbolic consumption context. Sensors. 20(17):5016.
7. Du Z, Hu YG, Buttar NA, Mahmood A. 2019. X-ray computed tomography for quality inspection of agricultural products: A review. Food Sci Nutr. 7(10):3146-3160.
8. Erkayman B, Erdem E, Aydın T, Mahmüt Z. 2023. New artificial intelligence approaches for brand switching decisions. Alexandria Eng J. 63:625-643.
9. Fan H. 2023. Research on innovation and application of 5G using artificial intelligence-based image and speech recognition technologies. J King Saud Univ Sci. 35(4):8.
10. Fan JS, Zhang L, Lv TX, Liu Y, Sun H, Miao K, *et al*. 2023. MEAI: An artificial intelligence platform for predicting distant and lymph node metastases directly from primary breast cancer. J Cancer Res Clin Oncol. 149(11):9229-9241.
11. Feng L. 2022. Application analysis of artificial intelligence algorithms in image processing. Math Probl Eng. 2022:7382938.
12. Greco D, D'Ascanio V, Santovito E, Logrieco AF, Avantaggiato G. 2019. Comparative efficacy of agricultural by-products in sequestering mycotoxins. J Sci Food Agric. 99(4):1623-1634.
13. Guan SP, Wang ZQ, Cao YL. 2023. A novel blockchain-based model for agricultural product traceability system. IEEE Commun Mag. 61(8):124-129.
14. Guo JL, Hao HC, Wang MD, Liu ZY. 2022. An empirical study on consumers' willingness to buy agricultural products online and its influencing factors. J Clean Prod. 336:130403.
15. Jia WS, Liang G, Jiang ZJ, Wang JH. 2019. Advances in electronic nose development for application to agricultural products. Food Anal Methods. 12(10):2226-2240.
16. Juan W, Tao YD. 2021. Reverse integration and optimization of agricultural products e-commerce omnichannel supply chain under Internet technology. Acta Agric Scand Sect B Soil Plant Sci. 71(7):604-612.
17. Khan ZA, Koondhar MA, Aziz N, Ali U, Liu TJ. 2020. Revisiting the effects of relevant factors on Pakistan's agricultural products export. Agric Econ-Zemedelska Ekonomika. 66(12):527-541.
18. Li XQ, Yang JS, Ma JW. 2020. Large scale category-structured image retrieval for object identification through supervised learning of CNN and SURF-based matching. IEEE Access. 8:57796-57809.
19. Liu D, You J, Wang RB, Deng HY. 2022. Agricultural production optimization and marginal product response to climate change. Agric Basel. 12(9):1403.
20. Liu LP, Luo GQ. 2022. Quality inspection method of agricultural products based on image processing. Traitement Du Signal. 39(6):2033-2040.
21. Lu JW, Dai LH. 2023. Examining the threshold effect of environmental regulation: The impact of agricultural product trade openness on agricultural carbon emissions. Sustainability. 15(13):10048.
22. Liu YQ, Xu SW, Liu JJ, Zhuang JY. 2022. Analytical bi-level multi-local-world complex network model on fresh agricultural products supply chain. Int J Agric Biol Eng. 15(1):208-215.
23. Liu YY, Guo XY. 2018. Mechanism of cooperative performance improvement in agricultural product supply chain based on behavioral cognitive science. NeuroQuantology. 16(5):580-587.
24. Lu JW, Dai LH. 2023. Examining the threshold effect of environmental regulation: The impact of agricultural product trade openness on agricultural carbon emissions. Sustainability. 15(13):10048.
25. Ma C, Wang DY, Hu ZQ, Li Z. 2018. Considerations of constructing quality, health and safety management system for agricultural products sold via e-commerce. Int J Agric Biol Eng. 11(1):31-39.
26. Maeda-Yamamoto M, Ohtani T. 2018. Development of functional agricultural products utilizing the new health claim labeling system in Japan. Biosci Biotechnol Biochem. 82(4):554-563.
27. Momin A, Kondo N, Al Riza DF, Ogawa Y, Obenland D. 2023. A methodological review of fluorescence imaging for quality assessment of agricultural products. Agric Basel. 13(7):1433.
28. Nguyen LT, Nanseki T, Chomei Y, Uenishi Y, Mi J. 2022. Determinants of product innovation implementation in

Japanese agricultural corporations. J Fac Agric Kyushu Univ. 67(2):239-247.

29. Saghaian S, Mohammadi H, Mohammadi M. 2022. The effects of agricultural product exports on environmental quality. Sustainability. 14(21):13857.
30. Sánchez-Morales LN, Alor-Hernández G, Rosales-Morales VY, Cortes-Camarillo CA, Sánchez-Cervantes JL. 2020. Generating educational mobile applications using UIDPS identified by artificial intelligence techniques. Comput Stand Interfaces. 70:103407.
31. Santos RPD, Prado H, Neto ISA, de Oliveira GAA, Silva AIV, Zenóbio EG, *et al*. 2021. Automated identification of dental implants using artificial intelligence. Int J Oral Maxillofac Implants. 36(5):918-923.