RESEARCH ARTICLE

Agricultural product brand value evaluation method and application based on big data

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With the development of big data technology, effective brand value assessment of agricultural products has become a key competitive capability. Based on big data analysis, this study established an agricultural product brand value evaluation model around the influence of brand awareness, brand image, consumer loyalty, and brand association on brand value. The model was trained and validated using linear regression techniques by analyzing data collected from multiple sources including social media, online shopping platforms, and consumer surveys. The results showed that the model could accurately predict the brand equity of agricultural products, in which brand awareness and consumer loyalty were the main factors affecting brand equity. On this basis, the study put forward specific strategies to enhance the brand equity of agricultural products. Although the study had some limitations, such as sample size and linear assumptions of the model, it provided a new perspective for the evaluation of agricultural brand equity and guidance for the practice of agricultural brand management.

Keywords: brand value; agricultural products; big data analysis; consumer behavior; brand management.

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Introduction

In today's rapidly developing market environment, the brand value of agricultural products has become a key area of agricultural economic research. Brand value is not only related to the market performance of the product, but also affects the purchase decision of consumers and the long-term sustainable development of the brand. With the development of globalization and information technology, especially the rise of big data technology, the value assessment and management of agricultural products brands are facing new challenges and opportunities. Traditional methods of agricultural product brand value evaluation often rely on limited market data and consumer research, which are limited in data quantity and data dimension. However, the application of big data technology provides a richer and multidimensional data source for brand value assessment of agricultural products. By analyzing large-scale user behavior data, market transaction data, and social media data, it is possible to gain a more comprehensive understanding of consumer preferences, brand market performance, and competitive environment.

The current evaluation of brand value has shifted from the traditional market research method to the comprehensive evaluation model using big data technology. Wang *et al*. discussed the innovative design and evaluation of agricultural machinery products, emphasizing the role of design innovation in enhancing product value [1]. In addition, Du *et al*. conducted sustainable evaluation of agricultural product suppliers through IFAHPTODIM model, highlighting the importance of decision model in supply chain management [2]. In terms of agricultural product packaging evaluation, the researcher proposed a new evaluation method based on structural similarity and MTF, which demonstrated the application potential of structured methods in visual evaluation [3]. Further, scientist assessed the risks of agricultural cold chain logistics from the perspective of ecological economy, providing a new perspective for cold chain management [4]. A study used big data to evaluate the e-commerce of agricultural products, which further confirmed the wide application of data analysis in the agricultural field [5]. These studies showed that big data and quantitative models had great potential in assessing the brand value of agricultural products, not only to enhance the value of products and services, but also to optimize supply chain management and cold chain logistics. Additionally, these studies constituted the academic support and theoretical basis of the research on the evaluation method of agricultural products brand value.

The purpose of this study was to explore and develop a brand value evaluation method of agricultural products based on big data technology, which combined the advantages of big data analysis such as processing large amounts of data and revealing hidden consumer behavior patterns to provide a more accurate and comprehensive framework for brand value assessment. This research would enrich the current academic discussion on brand value assessment, especially methodological innovation in the context of big data and was expected to provide new perspectives for brand value assessment of agricultural products, especially in processing and interpreting large data sets [6-8]. The results of this study would not only fill the gap in the field of brand value assessment of agricultural products academically, but also provide practical strategies for brand management of agricultural products in practice, which was of great value for promoting the modernization and monetization of agricultural industry.

Materials and methods

Questionnaire design

To ensure the validity and reliability of the data in the questionnaire design, the following principles were adhered including (1) the clarity that the questionnaire focused closely on the research aims to ensure each question related to the objectives of the agricultural product brand value assessment; (2) simplicity that questions were concise and straightforward, avoiding excessively long or complex statements to ensure ease of understanding for respondents; (3) unbiased that avoiding leading language to ensure neutrality and objectivity; (4) quantifiable repeatability that using quantified five-point or seven-point scales to facilitate subsequent data analysis. Additionally, the questionnaire had wide coverage, encompassing all aspects related to the brand value of agricultural products including brand awareness, brand image, and consumer satisfaction. It was crucial to ensure applicability and universality, which made the questionnaire suitable for respondents from diverse backgrounds with universally understandable language.

Data sources and collection

To fully assess the brand value of agricultural products, various data sources and collection channels were employed in addition to questionnaires. Key data acquisition channels included social media platforms that analyzed consumer discussions and feedback to reveal brand reputation and consumer perception. Online shopping platforms also provided valuable data on agricultural product sales and consumer reviews from e-commerce websites [9, 10]. In addition, market reports and industry research offered professional analysis and market insights, in which data released by governments and industry associations provided macro market trends and industry dynamics. Together, these diverse sources offered a comprehensive view of the brand value of agricultural products. According to different data channels, specific collection methods were adopted. Data crawlers and apis were used to collect posts and comments mentioning brands from social media platforms to obtain qualitative and quantitative data including the number of posts mentioning brands and consumer sentiment analysis. Grab sales data and consumer reviews from online shopping platforms were used to obtain quantitative data including sales volume, user ratings, and reviews. The databases and market reports were used to obtain quantitative and qualitative data for market share and growth rate [11]. By accessing and downloading government data through public databases, quantitative data on industry production and sales could be collected. Customer interviews arranged in person or online could provide qualitative data such as consumers' in-depth opinions and suggestions on the brand. By combining the above multiple channels and methods, multi-dimensional data on the brand value of agricultural products were collected, which was crucial for subsequent analysis and evaluation.

Data processing and preliminary analysis

Data cleaning and teleprocessing are key steps in data analysis to ensure data quality and consistency, which include missing value processing, outlier detection and processing, data format unification, data conversion, and data normalization or standardization. Missing value processing involves examining and processing missing values in the data and selecting appropriate methods to fill in or remove the missing data. The purpose of outlier detection and handling is to identify and deal with outliers that may be caused by entry errors or other atypical conditions. Data format unification ensures that all data follows a uniform format such as date format and numerical standards [12]. Data transformation encodes classified data into numerical form as needed for easy analysis. Data normalization or standardization is the normalization or standardization of data, especially when using certain algorithms to ensure that the data is in the same order of magnitude. Through these steps, the quality of the data can be improved, and a solid foundation can be laid for subsequent analysis. In this study, the missing value processing used the mean or median numbers to fill in. For outlier processing, the abnormal data was eliminated or corrected. Data format unification was used to unify date and number formats. Data conversion involved converting non-numerical data to numerical values, while data normalization or standardization normalized all score data to a 0-1 range by adjusting the data range. Together, these steps ensured data consistency and accuracy, providing a reliable basis for subsequent analysis [13, 14]. The preliminary data analysis included descriptive statistical analysis, data visualization, correlation analysis, and preliminary trend analysis. Descriptive statistical analysis calculated basic statistics such as mean, median, and standard deviation. Data visualization presented data in different types of charts. Correlation analysis detected correlations between data using Pearson correlation coefficient. Preliminary trend analysis identified key trends and patterns in the data [15]. Through these steps, the quality of the data collected was ensured and the valuable information could be extracted, which laid the foundation for subsequent in-depth analysis.

Principles of model design

The basic principles of model design in this study included that the model should be (1) consistent with the existing brand value theory and reflect all aspects of brand value, (2) able to adapt to the type and structure of data collected, (3) with clear and easy understand results to facilitate interpretation and application, (4) to accurately predict or evaluate the brand value of agricultural products, (5) not too complex to avoid over-fitting, and (6) allowing for validation and testing. A linear model based on consumer survey data was designed for brand value of agricultural products evaluation by considering brand perception, brand image, consumer loyalty, and brand association as independent variables, and brand value as dependent variables. The model was expressed in equation (1) below.

$$\text{Brand Value } = \beta_0 + \beta_1 \times \text{ Brand Awareness } + \beta_2 \times \text{ Brand Image } + \beta_3 \times \text{ Consumer Loyalty } + \beta_4 \times \text{ Brand Association } + \varepsilon \quad (1)$$

where β_0 was the intercept item. β_1, β_2, β_3, and β_4 were model parameters, representing the degree of influence of each variable on brand value. ε was the error term, representing the effect of other unobserved factors. All these variables were quantitatively assessed using a scale of 1 to 5. Brand value was the output result of comprehensive evaluation. By analyzing the size and sign of the coefficient of each variable, it could indicate the change amount of brand value when the corresponding independent variable was increased by one unit. The model could be verified and adjusted using actual data to optimize the evaluation of brand value.

Parameter selection and model setting

The parameter selection is a key step to ensure the accuracy and reliability of the model [15], which involved deciding which variables should be included in the model and how to set those model parameters to best fit the data. The selection of parameters should be based on theoretical guidance and the results of previous research to ensure that the selected parameters had a significant impact on brand value. Data mining techniques such as correlation analysis and feature selection algorithms were applied to identify which variables were the most relevant to brand value. While ensuring the accuracy of the model, overly complex models should be avoided to prevent overfitting, and statistical methods were used to determine whether the model parameters were significant to ensure the statistical validity of the model. The parameter selection and model setting for the linear regression model could be expressed as follows.

$$\text{Brand Value } = \beta_0 + \beta_1 \times X_1 + \beta_2 \times X_2 + \ldots + \beta_n \times X_n + \varepsilon \quad (2)$$

where $X_1, X_2, ..., X_n$ were the selected parameters such as brand awareness, brand image, *etc*. $\beta_1, \beta_2, ..., \beta_n$ were the corresponding coefficient, while β_0 was the intercept term and ε was the error term. Parameter selection was based on the relevance and importance of the variable to brand value. Brand perception was selected because of its high correlation with brand value. The brand image was included because of its significant impact on brand value. Consumer loyalty was a key factor supported by theory and data, and brand association was important in theory but needed to be verified by data. In practical applications, the coefficient values would be obtained through data analysis such as estimating parameters in a linear regression model using the least square method. The estimate for each coefficient would indicate how much the brand value could be expected to change for each one-unit change in the corresponding independent variable, holding all other variables constant. These parameters and model settings would ultimately be validated and adjusted with empirical data to ensure the accuracy and reliability of the model.

Model training and verification process

In this study, the model was trained on one set of data and validated on another set of data to test its generalization ability and accuracy [16, 17]. Model training usually involved using a portion of data, often called a training set, to estimate model parameters and could be expressed below.

$$\min_\beta \sum_{i=1}^{n} \left(y_i - (\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_n x_{in}) \right)^2 \quad (3)$$

where y_i was the actual brand value of the i observed value. $x_{i1}, x_{i2}, ..., x_{in}$ were the independent variable associated with the i observation. Model validation involved testing the accuracy of the model on another set of data (validation set), which helped to evaluate

Table 1. Simulation model training and validation data resources.

Database	Organization	City	Province/State	Country	Data volume	Collection duration	Training data (%)	Validation data (%)
Agri Data Hub	Agricultural Big Data Research Center	Beijing	Beijing	China	500,000	Jan 2022 - Jan 2023	80%	20%
Consumer insights	Consumer Insights Research Institute	Shanghai	Shanghai	China	300,000	Mar 2022 - Mar 2023	75%	25%
E-market analytics	E-commerce Market Analysis Platform	Guangzhou	Guangdong	China	450,000	Feb 2022 - Feb 2023	70%	30%
Social media trends	Social media Trends Analysis Center	New York	New York	USA	600,000	Apr 2022 - Apr 2023	85%	15%
Market research reports	Market Research Reports Center	London	England	UK	250,000	May 2022 - May 2023	80%	20%

whether the model could generalize new data that was not involved in the training. The verification process usually involves calculating the difference between the predicted value and the actual value as measured. By comparing the predicted and actual values, the accuracy and validity of the model could be assessed.

Multidimensional data from five major databases were used for this study, which included the key indicators of brand perception, brand image, consumer loyalty, and brand association, ensuring the breadth and diversity of the data (Table 1). The Agri Data Hub mainly included information on agricultural sales, market share, and consumer evaluation. Through these data, a comprehensive understanding of the sales performance and consumer feedback of each brand in the market could be obtained. Consumer insights covered information on consumer buying behavior and brand loyalty. This data was helpful for in-depth analysis of the purchasing decision-making process of consumers and the formation of brand loyalty. E-market analytics included sales data and consumer feedback from e-commerce platforms. Through this database, it was possible to analyze a brand's performance in the online market and its appeal to consumers. Social media trends consisted mainly of brand discussions and consumer sentiment analysis on social media, which helped to understand a brand's reputation on social media and the emotional leanings of consumers. Market research reports covered industry analysis and market trends. The macro trends within the industry and the market position of the brand could be obtained through it.

Results and discussion

Data analysis and model evaluation

The process of data analysis and model evaluation involved identifying the most influential variables in the model, explaining how these variables affected the predictions, and the overall performance of the model [18, 19]. The results showed that certain variables such as brand perception and consumer loyalty demonstrated a significant impact on predicting brand value. Further, the R-squared value (R^2) suggested that the model could explain most of the brand value variability. The mean square error (MSE) index indicated the accuracy level of the model prediction and the deviation between the predicted results and the actual data (Figure 1). The results confirmed that brand awareness had the strongest positive impact on brand value

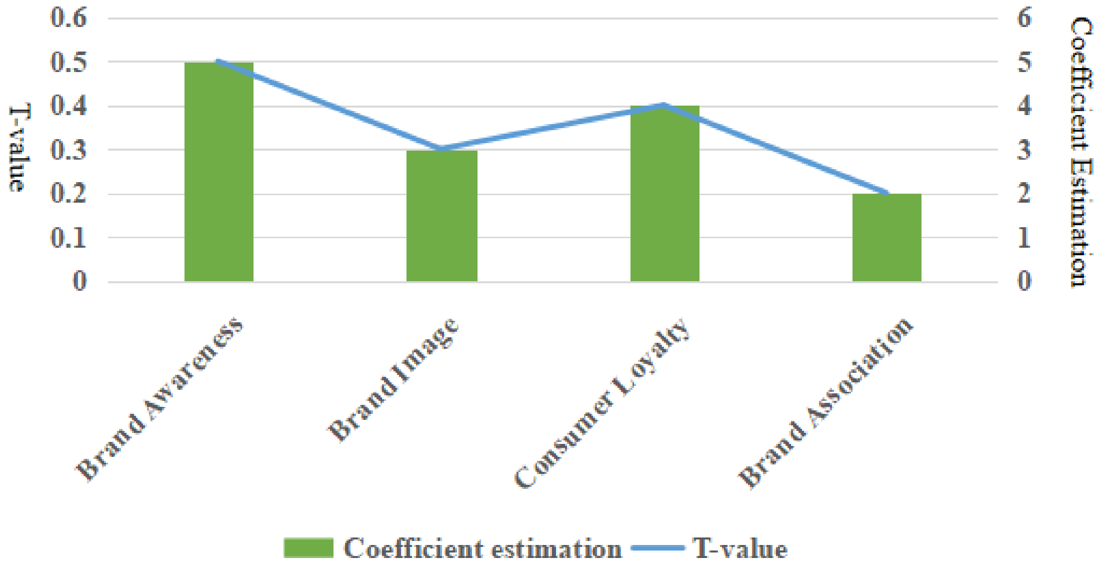

Figure 1. Significant analysis of variables.

with the highest coefficient, indicating that, among all the variables considered, improving brand awareness could significantly increase brand value. Consumer loyalty was also an important indicator with a high positive impact, indicating that loyal customers were crucial to the improvement of brand value. Although the influences of brand image and brand association were small, they were still significant and should be paid attention to in the brand strategy. The R^2 value of the model was 0.80, indicating that the model could explain most changes in brand value, which was evidence of the model's good explanatory power. These findings had practical implications for developing strategies as they provided concrete ways to increase brand value. Brand managers might invest more resources in improving brand awareness and maintaining consumer loyalty to enhance overall brand value.

The model performance analysis was to evaluate the performance of the constructed model in predicting and interpreting data. Important performance metrics included MSE, R^2, and Adjusted R-squared value (Adjusted R^2). These indicators provided a quantitative assessment of the model's accuracy and explanatory power. MSE was an average measure of the difference between the model's predicted and actual values as shown in equation (4), while R^2 was the proportion of data variability that reflected the model's interpretation as shown in equation (5).

$$\mathrm{MSE} = \frac{1}{m}\sum_{i=1}^{m}\left(y_i - \hat{y}_i\right)^2 \tag{4}$$

where *m* was the number of samples. y_i was the actual value. $\hat{y}_i$ was the predicted value.

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{m}\left(y_i - \bar{y}\right)^2} \tag{6}$$

where $\bar{y}$ was the mean of the actual values. The Adjusted R^2 was to consider the number of variables in the model, which provided a more rigorous evaluation of model performance with the equation as below.

$$\text{Adjusted } R^2 = 1 - \frac{\left(1 - R^2\right)(m-1)}{m-n-1} \tag{6}$$

where *n* was the number of variables in the model. The results of this study showed that the value of MSE was 0.25, indicating that the average error of the model prediction was 0.25. The smaller the value, the higher the prediction accuracy of the model. The value of R^2 was 0.80, indicating that the model could explain 80% of the total variability of the data, while the adjusted R^2 was 0.78. The closer of R^2 value to 1 was, the more explanatory the model was. These indicators suggested that the model had high predictive accuracy and explanatory ability and was an effective tool to evaluate the brand value of agricultural products. However, there was still room for improvement, especially in terms of reducing forecast errors.

Model efficiency and optimization strategy

The results showed that the model had some predictive power, but still had room for improvement. Common optimization strategies included feature engineering, adjusting model parameters, cross-validation, model integration, and data augmentation. Feature engineering involved reevaluating and selecting model features, which might include adding new features or removing less significant features. Adjusting model parameters such as regularization parameters could be particularly effective in reducing overfishing and improving generalization. Using cross-validation methods such as K-fold cross-validation, the generalization ability of the model could be evaluated. Model integration techniques such as random forests or gradient hoists could improve model performance. Adding data samples or using data enhancement techniques could improve the stability and accuracy of the model. Through these methods, the model could be further optimized to improve its effectiveness and accuracy in practical applications. Optimization strategies needed to be selected and adjusted according to the actual performance of the model and application scenarios.

Brand value evaluation

Through the analysis of the multi-dimensional datasets, the evaluation result of the brand value of agricultural products was obtained. Three products branded "Qingtian Organic", "Pastoral", and "Green Wiz" were examined in this study with their brand values as 67.3, 59.7, and 52.1, respectively, based on the comprehensive analysis of four main indicators including brand awareness, brand image, consumer loyalty, and brand association. In terms of brand awareness, "Qingtian Organic" scored 84.1, while "Pastoral" scored 72.6 and "The Wizard of Oz" scored 63.4, which indicated that "Qingtian Organic" had invested a lot in marketing and consumer education, making its awareness significantly higher than other brands. "Pastoral" had improved its popularity through a series of marketing activities, but the effect was slightly worse than "Qingtian Organic". Recognition of "The Wizard of Oz" was relatively low due to limited market coverage. In the brand image evaluation, the scores of "Qingtian Organic", "Pastoral", and "Wizard of Oz" were 78.3, 64.9, and 58.7, respectively. "Qingtian Organic" had a clear and attractive image in the minds of consumers and widely promoted the concept of green environmental protection. The brand image was deeply rooted in people's minds. "Pastoral" had some achievements in image building, but it needed to further improve its brand story and visual identity system. "Wizard of Oz" was in the brand image of the general performance, which needed to strengthen the brand image construction. In terms of consumer loyalty, "Green Field Organic" scored 75.4, "Pastoral" scored 68.2, and "Wizard of Oz" scored 57.9. The high loyalty of "Qingtian Organic" came from its high-quality products and good after-sales service, which had cultivated many loyal customers. "Pastoral" had a certain accumulation in user experience and a high customer buyback rate, but it still needed to further improve customer loyalty management. The performance of "Wizard of Oz" in consumer loyalty was relatively average, and it was necessary to strengthen customer relationship management and after-sales service quality. For brand association, "Qingtian Organic" scored 80.7, "Pastoral" scored 70.5, and "Wizard of Oz" scored 62.8. "Qingtian Organic" had successfully linked the brand with an organic, healthy, and high-quality image, while "Pastoral" had made some progress in brand association. However, "Wizard of Oz" had not yet formed a strong brand association in the minds of consumers and needed to further shape the brand story and brand culture. The results indicated that "Qingtian Organic" had excellent performance in four aspects of brand awareness, brand image, consumer loyalty, and brand association and has the highest brand value. Although "Pastoral " had a certain foundation in these aspects, it still needed to be further improved. The "Wizard of Oz" needed to strengthen brand building in all aspects to enhance its overall brand value.

Comparative analysis between different brands

A comparative analysis was performed to reveal the differences among brand values and their respective advantages and disadvantages. In terms of brand awareness, "Qingtian Organic" was far ahead of other brands with 84.1 points mainly due to its large-scale marketing and high frequency of brand promotion activities followed by "Pastoral" with 72.6 points, while it gradually increased its brand awareness by holding several agricultural trade fairs and participating in national agricultural fairs. "The Wizard of Oz" had a relatively low recognition score of 63.4 mainly due to its small market coverage and lack of a strong branding strategy. For brand image, "Qingtian Organic" scored 78.3, which was highlighted by its green and organic brand positioning and strict quality control, so that it formed a high-quality image in the minds of consumers. "Pastoral" scored 64.9 with a more traditional brand image. Although the product quality was reliable, but lack of innovation and modern sense. "Wizard of Oz" scored 58.7 with a relatively vague brand image. Consumers lacked awareness of its characteristics, therefore, it needed to strengthen brand positioning and image building. In terms of consumer loyalty, "Qingtian Organic" once again led the way with 75.4 points, reflecting its excellent performance in customer relationship management and after-sales service. Its high-quality products and excellent customer service had won the trust and loyalty of consumers. With a score of 68.2, "Pastoral" had gradually increased consumer buyback rates and satisfaction through a range of membership activities and loyalty programs. With a score of 57.9, "Wizard of Oz" was mediocre with low consumer loyalty and an urgent need to improve customer experience and after-sales service. For brand association, "Qingtian Organic" scored 80.7, successfully associating the brand with organic, healthy, high quality, and other images, forming a strong brand association. "Pastoral" scored 70.5 with the brand association mainly focused on traditional, rural, and natural, but lacked modern sense and innovation. "Wizard of Oz" scored 62.8. The brand association was relatively scattered, failed to form a distinct brand characteristic, and needed to strengthen the brand story and culture shaping. The comparison results showed that "Qingtian Organic" had outstanding performance in brand recognition, image, loyalty, and the overall brand value was the highest one. "Pastoral" had a certain foundation in brand building, but it needed to be further improved in terms of innovation and modernization. "Wizard of Oz" needed to strengthen brand building in all aspects, enhance brand awareness and consumer loyalty, improve its market competitiveness and brand value.

Discussion

Advantages and disadvantages of the evaluation model

The big data-driven brand value evaluation model adopted in this study showed significant advantages and some shortcomings in practice. The model comprehensively evaluated the value of agricultural products brands by integrating multi-source data and using key indicators such as brand awareness, brand image, consumer loyalty, and brand association. The model demonstrated that the diversity and universality of the data improved comprehensiveness and accuracy of the evaluation results. By collecting multiple data sources such as social media, online shopping platforms, market reports, and consumer surveys, the model was able to fully capture the performance of the brand in the market and the real feedback of consumers. The brand "Qingtian Organic" had performed well in several indicators, showing its leading position in comprehensive brand value. This multi-dimensional data acquisition and analysis method could effectively avoid the bias and misdirection that may be brought by a single data source. The model used machine learning algorithm and statistical analysis technology to enhance the scientific and predictive ability of brand value assessment. Through the weight allocation and optimization of each index, the model could accurately reflect the actual market performance and consumer attitude of the brand. For example, the high weight setting of brand image and consumer loyalty in the model successfully revealed the advantages of "Qingtian Organic" in these two aspects to evaluate its brand value reasonably. However, the model also had some shortcomings. The quality of data and the timeliness of data acquisition had a great impact on the evaluation results of the model. Although multi-source data could provide rich information, the inconsistency of data and the timeliness of collection might lead to the deviation of evaluation results. The brand "Wizard of Oz" might not reflect its latest market performance on some indicators due to the lack of timely data updates. Models can face challenges when dealing with qualitative data. While quantitative data could be processed with statistical precision, qualitative data such as consumer reviews and brand associations could be subject to a certain amount of subjectivity and uncertainty when translated into quantifiable metrics, which posed a challenge to the reliability of the evaluation results, especially for indicators such as brand image and consumer sentiment that involved more subjective evaluation. The complexity and calculation cost of the model were high. In the context of big data, data processing and analysis required strong computing power and resource support, which put forward requirements for cost and efficiency in practical applications. The evaluation model in this study had significant advantages in multidimensional data integration and scientific evaluation, but it still needed to be further optimized in data quality control, qualitative data processing, and computational cost management. Through continuous improvement and optimization, the model could better serve the evaluation of brand value of agricultural products and the formulation of market strategies.

Application suggestions for brand management of agricultural products

The results of this study suggested improving brand awareness through marketing activities and advertising since brand awareness had a significant impact on brand value. Also, in view of the importance of consumer loyalty, it is recommended to maintain and enhance consumer loyalty by improving product quality, optimizing customer service, and launching loyalty programs. In addition, although the brand image had a small impact, it was still important in shaping consumers' purchasing decisions. Therefore, It was recommended to reinforce the positive brand image through social responsibility activities and brand stories. Further, brand association had a certain positive impact on brand value, which could be enhanced by partnering with other well-known brands or sponsoring related events. Based on the results of model evaluation, some application suggestions for brand management of agricultural products were put forward, which included increasing brand awareness and market visibility of the brand to enhance brand value by increasing advertising investment and utilizing social media, strengthening brand loyalty, stabilizing and enhancing brand value by increasing repeat purchase rate including improving product quality and optimizing after-sales service, optimizing the brand image and enhancing the brand appeal by enhancing the public's positive impression of the brand through social responsibility activities and shaping the brand story, and using brand associations to establish positive associations with other brands or events and increasing brand added value through brand partnerships and sponsored events. The implementation of those recommendations needed to be reviewed and evaluated regularly to ensure that they were effective in enhancing the value of agricultural products brands. Through this feedback loop, brand management could be continuously optimized to stay ahead in a competitive market.

Conclusion

This study applied big data technology and statistical analysis methods to evaluate the value of agricultural product trademarks. By constructing and analyzing a data-driven model, the influence of brand awareness, brand image, consumer loyalty, and brand association on the brand equity of agricultural products were discovered. The analysis of model performance showed that the linear regression model could effectively predict brand equity and had high explanatory power. In addition, the results provided a series of practical application suggestions for brand management of agricultural products such as improving brand awareness and strengthening brand loyalty to help brand managers enhance brand value. This study made some achievements in both theory and practice. However, there were still some limitations, which included the size of collected sample that might limit the wide applicability of the model and the model mainly relying on linear relationship assumptions that might not fully reflect complex nonlinear relationships. Due to these limitations, future studies may consider using larger and more diverse datasets to improve the generality of the study. In addition, exploring more complex models such as machine learning algorithms may reveal deeper brand equity dynamics. The comparative study of different regions or different types of agricultural products brands is also a useful direction for future research. This study provided new insights for brand value assessment of agricultural products based on big data and specific guidance and suggestions for brand management practice. It also put forward some suggestions for the future research direction, hoping to deepen and broaden the research in this field.

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