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Safety evaluation of genetically modified crops: consumer acceptance and market impact

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RESEARCH ARTICLE

Abstract

This study focuses on the application of genetically modified (GM) crops in modern agricultural production, delving into the assessment of their safety and consumer acceptance issues, while analyzing the mechanisms through which these factors influence market dynamics. The background highlights that, despite the potential of genetic modification technology to enhance the overall performance of crops, public concerns regarding their safety significantly affect consumer acceptance and, consequently, market performance. An evaluation of existing literature on the safety evaluation methods for GM crops is first conducted, identifying shortcomings in integrating consumer acceptance, and market dynamics. To address this gap, an evaluation system that incorporates consumer acceptance into the safety evaluation of GM crops was developed, utilizing the FuzzyID3 algorithm. Furthermore, employing multi-attribute decision theory, a decision model for assessing the stances of market stakeholders towards GM crops was established. This model, through the calculation and weighting of the distances from positive and negative ideal solutions across various modules, offers a novel perspective for market analysis. The methodology employed herein provides a robust tool for the safety evaluation and market forecasting of GM crops, holding practical value for guiding policy formulation and industry development.

Keywords: consumer acceptance; FuzzyID3 algorithm; genetically modified crops; market impact; multi-attribute decision theory; safety evaluation; stakeholders

Introduction

With the rapid development of biotechnology, genetically modified (GM) crops have become an integral part of modern agriculture, and their safety issues have consistently been a focal point of discussion among the public, scientists, and policymakers (Abikenova *et al.*, 2023; Akinbo *et al.*, 2015; Dwijendra *et al.*, 2023; Espolov *et al.*, 2023; Muthu and Devadoss, 2023; Oshergina and Ten, 2023; Raybould and Macdonald, 2018; Sonhaji *et al.*, 2022). The application of GM technology aims to increase crop yield, improve food quality, and enhance resistance to diseases and pests. However, potential ecological risks and impacts on human health remain key concerns for consumers (Bundschuh *et al.*, 2016). In the context of globalization, significant differences in the acceptance of GM foods among consumers from various countries and regions directly affect the market performance and industry development of GM crops (Oliver *et al.*, 2016; Pataer *et al.*, 2024a,b).

The safety evaluation of GM crops is a complex, multidimensional issue that involves not only scientific and technical risk assessments but also factors related to public psychology, social ethics, and market economics (Kamthan *et al.*, 2016; Liu, 2020; Safaei *et al.*, 2020). In order to promote the healthy development of GM technology, and gain consumer trust and acceptance, it is necessary to thoroughly investigate consumer acceptance and analyze its impact on the market (Fedorova and Herman, 2020). Therefore, research on the safety evaluation and consumer acceptance of GM crops not only aids in understanding the public's attitude towards GM foods but also plays a crucial role in shaping related policies and guiding industry development (Krizkovska *et al.*, 2022; Olabinjo *et al.*, 2020). Studies have found that consumer acceptance of GM foods is influenced by factors such as food safety, information transparency, and personal values. Transparent food labeling and scientific risk communication can increase consumer trust in GM foods. Additionally, many studies have shown that the cultivation of GM crops impacts agricultural ecosystems, including effects on soil microbial communities and soil quality. However, the specific extent and long-term effects of these impacts are still controversial.

Previous studies on the safety evaluation of GM crops have mostly focused on quantitative analyses in the fields of biology, ecology, and nutrition, often lacking a systematic and scientific evaluation of consumer acceptance (Koch *et al.*, 2016; Shin *et al.*, 2022, 2023; Suh *et al.*, 2024). Moreover, analyses of market impact frequently overlook the dynamic changes in stakeholders' positions and their profound influence on market decisions (Dolezel *et al.*, 2024; Haselmair-Gosch *et al.*, 2020; Safaei *et al.*, 2020). The absence of comprehensive consideration of both consumer psychology and market dynamics has made it difficult for existing research to fully reflect the reality of the GM crop industry.

This study aims to fill the existing research gap by first constructing an integrated safety evaluation index system for GM crops that takes into account consumer acceptance and scientifically assessing it using the FuzzyID3 algorithm. Secondly, the paper innovatively applies multi-attribute decision theory (Paul *et al.*, 2023), integrating longitudinal time-dynamic data into comprehensive index data, to assess the positions of various stakeholders in the GM crop market. By calculating the distances to positive and negative ideal solutions across modules and weighting them, a dynamic, mixed multi-attribute decision model is formed. This research not only provides a new theoretical method for the safety evaluation of GM crops but also offers a new perspective for understanding and predicting market trends, holding significant theoretical and practical value.

Genetically Modified Crop Safety Evaluation Considering Consumer Acceptance

The potential benefits and drawbacks of GM crops are a complex and controversial topic. On the potential benefits side, GM crops may offer a solution to global food security challenges. They can increase crop resistance to diseases and pests, boost yields, and reduce the need for pesticides, thereby helping to minimize the negative environmental impact of agriculture. Additionally, GM crops are hoped to improve nutritional values, increase food supplies, and help address hunger issues. However, we must also recognize the potential drawbacks of GM crops. Long-term environmental sustainability is a critical consideration. While GM crops may offer some benefits in the short term, their long-term effects remain unclear. For example, GM crops could reduce biodiversity in agricultural ecosystems, thereby affecting ecological balance. Furthermore, cultivating GM crops may lead to soil quality degradation, affecting the sustainable use of soil and adversely impacting long-term agricultural production. Therefore, when assessing the potential benefits and drawbacks of GM crops, both short-term and long-term impacts must be considered, especially in terms of environmental sustainability and biodiversity. Only by comprehensively balancing various factors can decisions be made that align with the goals of social and environmental sustainable development.

Consumer attitudes toward GM crops are influenced by a variety of complex factors, including cultural background, socioeconomic status, psychological cognition, and methods of information acquisition. From a cultural perspective, differences in attitudes towards nature and technology across different regions and countries could lead to varying levels of acceptance of genetic engineering technology. For example, some cultures might value traditional agricultural methods more and be conservative about new technologies. Socioeconomic factors are also crucial; consumers in better economic conditions may have easier access to extensive information about GM crops and may have more resources to choose non-GM products. Psychological factors, such as risk perception and trust in technology, also significantly influence people's attitudes. Additionally, the quality and direction of media reporting and public discussions can greatly shape consumer perceptions and choices. Therefore, a thorough analysis of consumer cognition needs to consider the interactions of these dimensions to fully understand the formation and change of people's attitudes towards GM products.

In constructing the safety evaluation index system for GM crops, four main dimensions were integrated: biosafety, nutritional value, environmental impact, and socio-economic effects, aimed at comprehensively assessing the safety of GM crops and public acceptance. The biosafety dimension includes sub-indicators such as the risk of horizontal gene transfer, potential allergenicity, and long-term health impacts. The nutritional value dimension considers the increase or decrease in nutrients provided by GM crops, and changes in food quality and taste. The environmental impact dimension assesses the effect of crops on biodiversity, the sustainability of farming systems, and their impact on non-target organisms. Lastly, the socio-economic effects dimension covers sub-indicators like consumers' right to be informed, labeling and product transparency, market acceptance of GM crops, and consumer preferences. Figure 1 displays the process of evaluating the safety of GM plants with consideration of consumer acceptance.

Researchers have used the FuzzyID3 algorithm to assess the potential risks of GM corn to the environment and human health. By constructing a composite index system that includes ecological impacts, health risks, and consumer acceptance, and utilizing a decision tree model enhanced with fuzzy logic to handle uncertainty and fuzzy data, they successfully classified and assessed the risks of various GM corn varieties. The results show that the model can effectively distinguish between high-risk and low-risk GM products, providing valuable safety information for regulatory bodies and consumers. The FuzzyID3 algorithm was selected for the evaluation of the safety of GM crops. This algorithm combines the advantages of fuzzy logic and decision trees, revealing the intrinsic relationships between different safety indicators through the construction of a decision tree model. It tolerates the incompleteness of input data, which is particularly important for capturing consumer preferences, as consumers may not provide all relevant decision-making information. Moreover, the algorithm adaptively learns and updates the evaluation model to accommodate constantly changing market feedback and consumer attitudes, thereby providing a more accurate, dynamic safety evaluation. This aids policymakers and agricultural producers in better understanding and predicting changes in consumer acceptance of GM crops, ensuring timely and effective decision-making. Figure 2 illustrates the decision tree construction process.

In applying the FuzzyID3 algorithm to construct the safety evaluation model for GM crops, key elements within the algorithm were defined. Non-leaf nodes represent core factors in the safety evaluation of GM crops, such as "long-term health impacts", "environmental impacts", "nutritional value", and "socio-economic impacts". Each non-leaf node is further associated with specific sub-attributes, for example, "long-term health impacts" may further divide into "potential allergenicity" and "risk of horizontal gene transfer". Candidate attributes are properties not yet used in dividing the dataset during the construction of the decision tree, such as "consumer right to know", "product labeling", and "market acceptance", which are assessed for their contribution to the safety evaluation to select the most appropriate attribute as a new decision node. Decision attributes represent the final evaluation outcome, such as "safe", "uncertain", and "unsafe". These attributes embody the final safety evaluation results processed through fuzzy logic, derived from

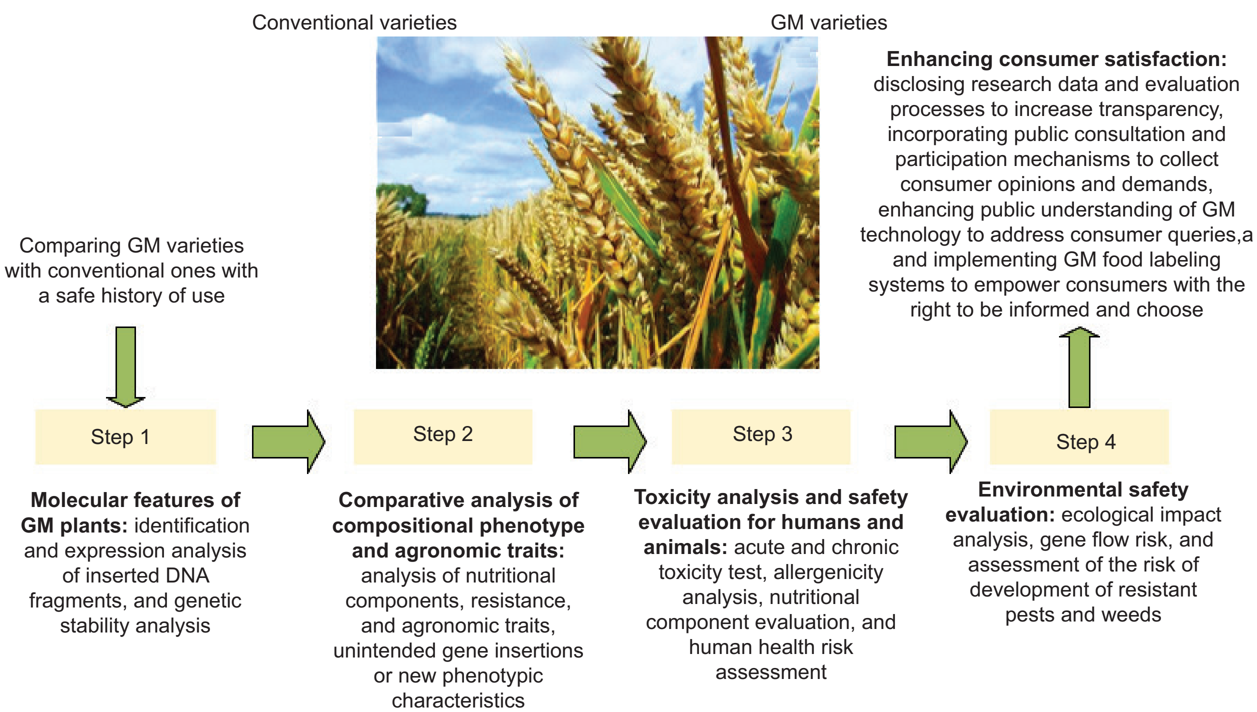

Figure 1. The safety evaluation process of GM plants considering consumer acceptance.

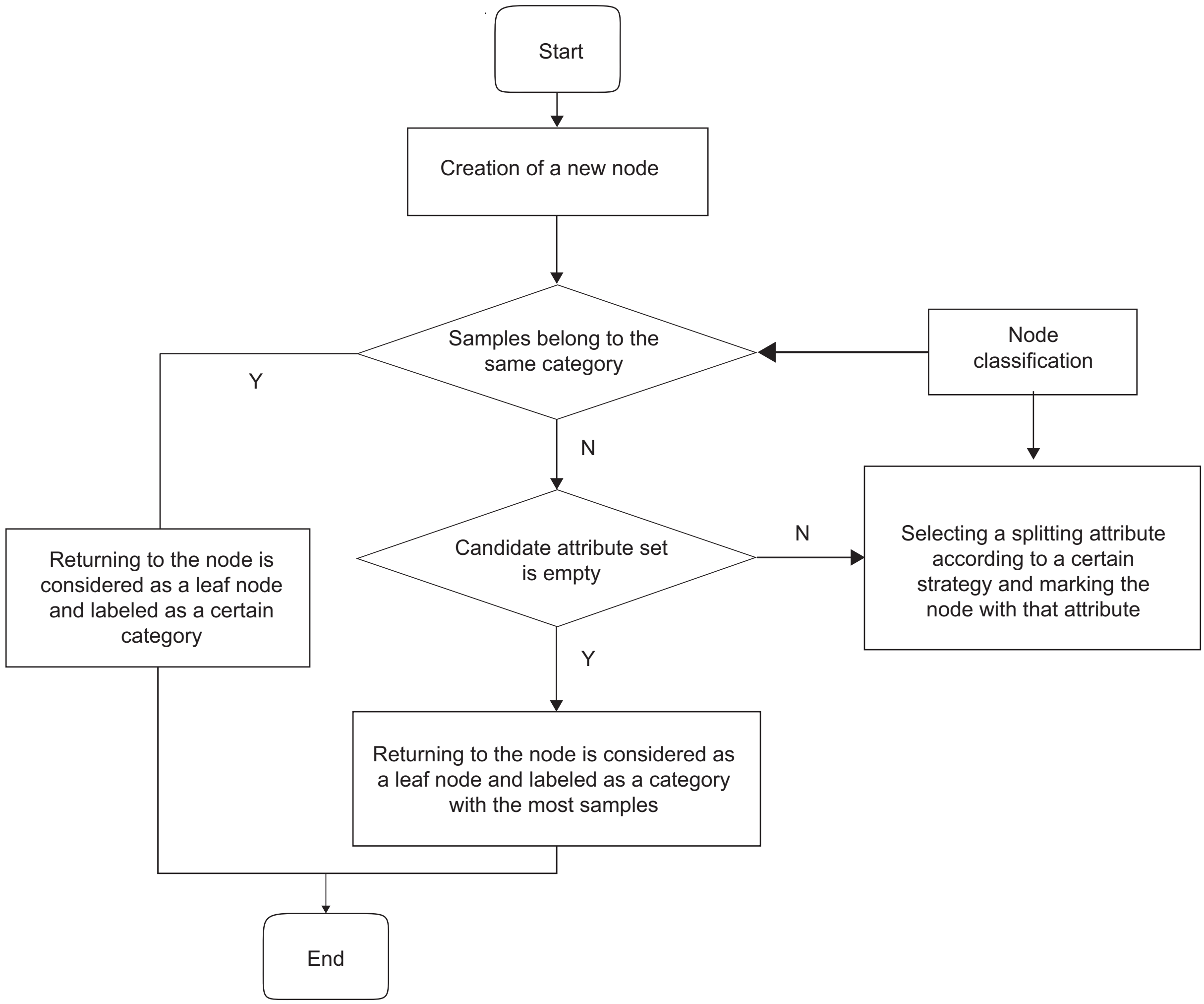

Figure 2. Decision tree construction process.

the model's path from root to leaf nodes. Specifically, for a non-leaf node T containing v candidate attributes $\{X_1, X_2, ..., X_v\}$, attribute $X_u (1 \leq u \leq v)$ has l_u fuzzy terms $\{S^1{}_u, S^2{}_u, ..., S^{lu}{}_u\}$, and decision attribute F has l fuzzy terms $\{F^1, F^2, ..., F^l\}$, with the cardinality measure of the fuzzy set represented by L.

In this study, the relative frequency of any candidate attribute value at a non-leaf node belonging to a certain fuzzy class is defined as the ratio of the number of data points in the dataset where the attribute value $S^j u (1 \leq u \leq v, 1 \leq j \leq l_u)$ belongs to the k-th fuzzy class $F^k (m \leq k \leq l)$ to the total number of data points at the non-leaf node T, represented as:

$$O_{uk}^{j} = \frac{L\left(S_u^j \cap F^k \cap T\right)}{L\left(S_u^j \cap T\right)} \tag{1}$$

The fuzzy information of a certain fuzzy attribute value at a non-leaf node is a measure of the classification uncertainty of the dataset for the given non-leaf node T attribute value S corresponding to the fuzzy class. This article quantifies and calculates the total uncertainty by considering the fuzzy entropy of data points belonging to each decision class, defined as:

$$U\left(S_u^j\right) = -\sum_{k=1}^{l} \log\left(O_{uk}^j\right) \tag{2}$$

The average fuzzy information of a certain fuzzy attribute value at a non-leaf node is the weighted average of all possible classification fuzzy information, where the weight is the relative frequency of each fuzzy class in the dataset. Assuming the weight of the i-th fuzzy attribute value in the fuzzy attribute X_u is represented by o_j, the following formula defines the average fuzzy information of the fuzzy attribute X_u at the non-leaf node T:

$$R(X_u, T) = \sum_{j=1}^{l_u} o_j U\left(S_u^j\right) \tag{3}$$

Information gain is the criterion for selecting the attribute to be used as the new decision node. The fuzzy information gain can be defined as the difference between the total fuzzy entropy of the dataset and the average fuzzy information of a given attribute value. The greater the fuzzy information gain of an attribute, the more it implies that using this attribute to divide the dataset will lead to the greatest reduction in uncertainty. The fuzzy information gain of the fuzzy attribute X_u at the non-leaf node T is defined as:

$$GAIN(X_u)L(T) - R(X_u,T) \tag{4}$$

Figure 3 presents an example of a decision tree classifying the factors affecting the safety of GM crops.

Assessment of Market Stakeholders' Positions on GM Crops Based on Multi-attribute Decision

Before constructing a model for assessing the positions of market stakeholders concerning GM crops, it is necessary to determine the relevant evaluation indicator system. The core stakeholders in this model include consumers, farmers, biotechnology companies, governments and regulatory bodies, environmental organizations, research institutions, and international trade partners. Hence, the constructed evaluation indicator system should comprehensively consider concerns and positions from various aspects such as ecological safety, economic benefits, health risks, legal regulations, ethics, social impact, technological innovation, market acceptance, and international cooperation and competition. This article sets specific quantitative indicators such as product safety test results, market share, consumer trust surveys, policy support strength, and biodiversity impact assessments to dynamically track and analyze changes in expectations and positions among stakeholders.

Multi-attribute decision theory was applied in a study on the market acceptance of GM crops. Researchers integrated market data from different periods, including consumer preferences, market prices, and regulatory changes, and used multi-attribute decision analysis tools such as the Analytic Hierarchy Process to calculate the weights of various factors and comprehensively assess the positions of different stakeholders. Through this approach, the study revealed the impacts of policy changes and increased public awareness of market attitudes, providing a scientific basis for formulating market strategies and policy adjustments. These cases demonstrate that the FuzzyID3 algorithm and multi-attribute decision theory are not only capable of handling complex and fuzzy data but also provide comprehensive and in-depth analysis, which is of significant practical value for the safety assessment and market analysis of GM

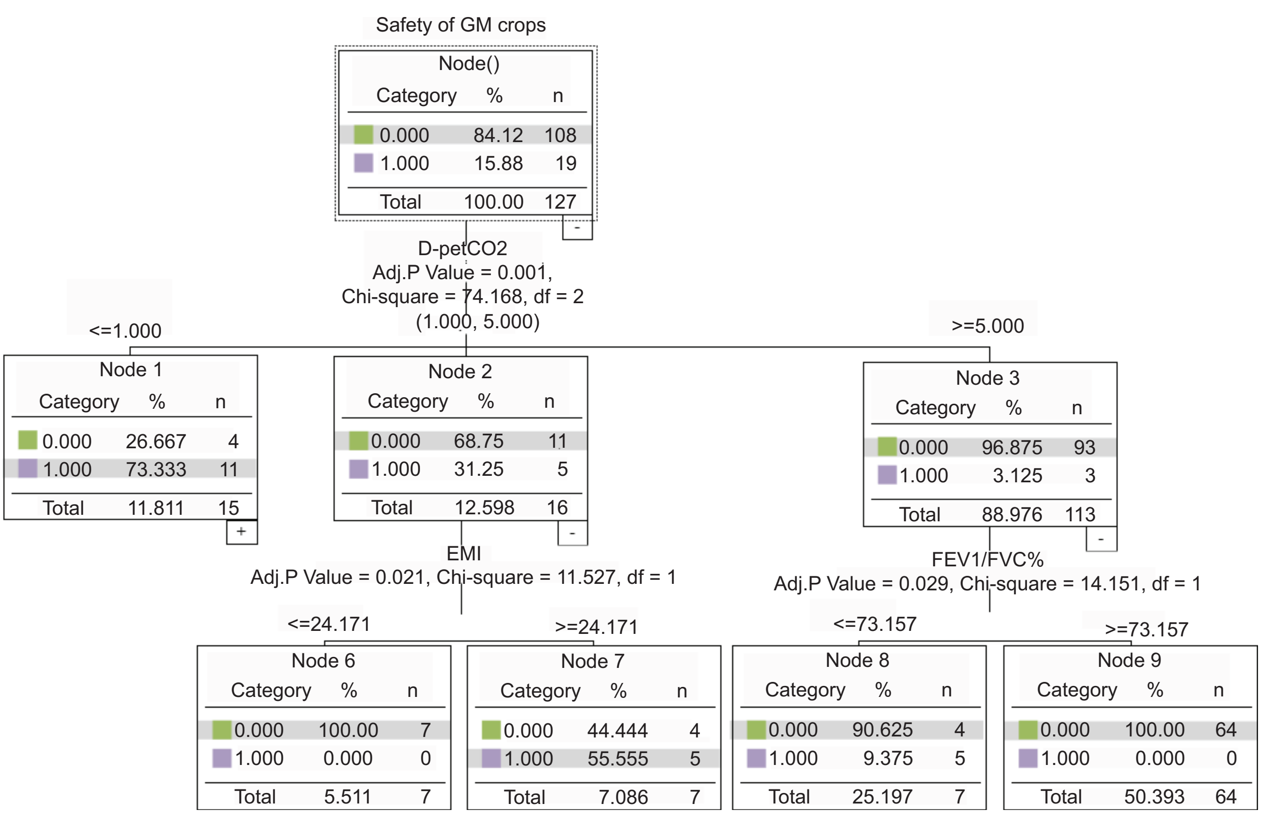

Figure 3. Example of a decision tree classifying factors affecting the safety of GM crops.

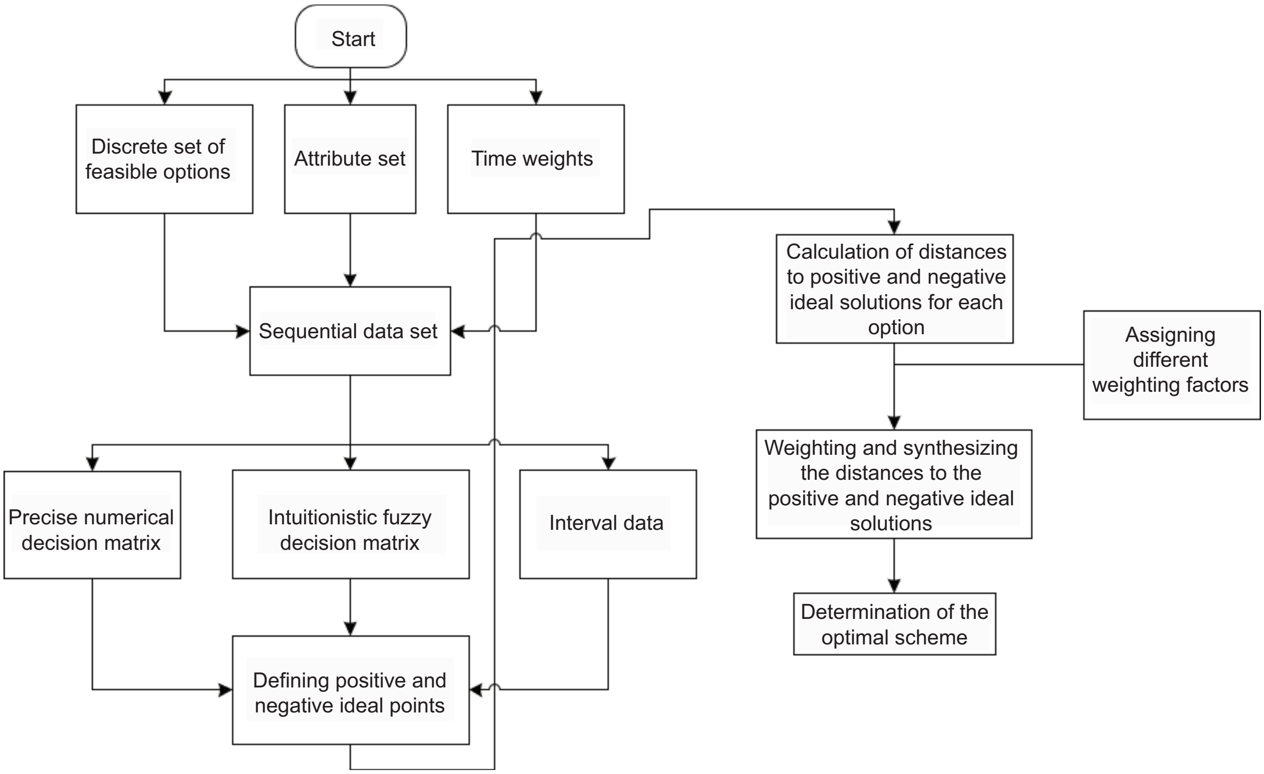

Figure 4. Model construction process.

crops. The study further constructs a model for assessing the positions of GM crop market stakeholders based on dynamic mixed multi-attribute decision-making, modularizing the diversified evaluation indicators, and classifying data according to indicator characteristics. In this model, data are first divided into different modules based on the nature of indicators such as ecological impact, economic benefits, and social acceptance, ensuring the effective capture and expression of information's multidimensionality and dynamism. Subsequently, the model integrates time-varying data from each module into comparable comprehensive indicators. Specifically, the distances of module indicator data from an ideal state are calculated, constructing positive and negative ideal solutions, thereby determining the closeness of each module's indicator data to these ideal solutions. By assigning different weight factors according to the importance and decision-making objectives of various stakeholders, the distances to the positive and negative ideal solutions from different modules are weighted and synthesized, ultimately forming a comprehensive decision value. Figure 4 displays the model construction process.

Temporal data set

The discrete set of feasible options is represented by $B = \{B_1, B_2, ..., B_v\}$, encompassing all possible promotion schemes for GM crops, such as different types of GM crops introduced to the market, various market promotion strategies, regulatory policies, and labeling systems. Each scheme aims to address the challenges associated with the safety and consumer acceptance of GM crops. The set of attributes is denoted by $H = \{H_1, H_2, ..., H_l\}$, with its weight vector represented by $\mu=(\mu_1, \mu_2, ..., \mu_l)^T$, where $\mu_b \geq 0(k = m, 2, ..., l)$ and the sum of the weights $\Sigma^l_{k=1}\mu_k = 1$. This set includes various indicators for assessing the relative merits of each scheme, such as safety test results, studies on the impact on consumer health, environmental impact assessments, economic cost-benefit analyses, consumer acceptance survey data, and market share forecasts. These attributes are designed not only to reflect performance in a single aspect but also to comprehensively represent the scheme's performance across multiple dimensions.

Given the long-term and ongoing impact of GM crops, the evaluation model necessitates assigning different weights to data from different time points or periods. Time weights can be established based on the severity of expected impacts, urgency, or the speed of policy response. For instance, in the short term, consumer acceptance and market impact might be prioritized, whereas, in the long term, ecological impacts and health risks may become the focus. o phases are represented by $S_j(j = 1, 2, ..., o)$, with their weight vector denoted by $\mu(s) = (\mu(s_1), \mu(s_2), ..., \mu(s_o))^T$, where $\mu_{(sj)} \geq 0(j = 1, 2, ..., p)$ and the sum of the weights $\Sigma o_{j=1}\mu(s_j) = 1$.

Each element of the precise numerical decision matrix represents a specific score or performance of a scheme on an attribute. In the context of evaluating the safety of GM crops, if reliable quantitative data are available, such as scientific experimental results or market sales data, these can be directly inputted into the precise numerical decision matrix. For example, the impact of a GM crop on non-target organisms obtained through experiments can be entered as a precise value in the decision matrix. Assuming the precise numerical decision matrix for the period s_j is represented by $F(s_j)^{*}=(f_{uk}(s_j))_{v*l}$, it can be expressed as $f_{uk}(s_j)=(a_{fuk}(s_j), A_{fuk}(s_j), ..., A_{fuk}(s_j))$. The vertical time-series values are compiled into comprehensive data according to time weights:

$$F^{*}=\sum_{j=1}^{s} F(s_j)^{*}\times\mu(s_j)=(f_{uk})_{v\times l} \tag{5}$$

The intuitionistic fuzzy decision matrix considers the degree of membership, non-membership, and hesitation for each scheme on every attribute to address uncertainty or ambiguity in decision-making. For subjective and potentially ambiguous evaluations such as consumer acceptance of GM crops, an intuitionistic fuzzy decision matrix can be utilized. For instance, consumer trust in the safety of GM foods can be represented by the degree of membership to indicate the level of acceptance, the degree of non-membership to represent the level of rejection, and the degree of hesitation to reflect consumer uncertainty. Assume the intuitionistic fuzzy decision matrix for the period s_j is represented by $F(s_j)^{\#}=(f_{uk}(s_j))_{v*l}$, where the attribute value expressed by intuitionistic fuzzy numbers is denoted by $f_{uk}(s_j) = (i_{fuk}(s_j), n_{fuk}(s_j), \tau_{fuk}(s_j))$, with $i_{fuk}(s_j)$ indicating the degree to which scheme B_u satisfies attribute H_k in period s_j, $n_{fuk}(s_j)$ indicating the degree to which scheme B_u does not satisfy attribute H_k in period s_j, and $\tau_{fuk}(s_j)$ representing the degree of uncertainty of scheme B_u towards attribute H_k in period s_j, within the same range as intuitionistic fuzzy variables, i.e., $i_{fuk}(s_j) \in [0,1]$, $n_{fuk}(s_j) \in [0,1]$, $i_{fuk}(s_j) + n_{fuk}(s_j) \leq 1$, $\tau_{fuk}(s_j) = 1 - i_{fuk}(s_j) - n_{fuk}(s_j)$, $(u = m, 2, ..., v; j = l, 2, ..., l)$.

Utilizing the DIFWA operator, all $F(s_j)^{\#} = (f_{uk}(s_j))_{v*l}$ are integrated into a comprehensive intuitionistic fuzzy decision matrix, represented by $F^{\#} = (f_{uk})_{v*l}$. The following expressions represent the elements of intuitionistic fuzzy numbers:

$$i_{uk}=1-\prod_{j=1}^{o}\left(1-i_{fuk(sj)}\right)^{\mu(sj)} \tag{6}$$

$$n_{uk}=\prod_{j=1}^{o} n_{fuk(sj)}{}^{\mu(sj)} \tag{7}$$

$$\tau_{uk}=\prod_{j=1}^{o}\left(1-i_{fuk(sj)}\right)^{\mu(sj)}-\prod_{j=1}^{o} n_{fuk(sj)}{}^{\mu(sj)} \tag{8}$$

$$f_{uk}=GUDQX_{\mu(s)}\left(f_{uk}\left(s_1\right),f_{uk}\left(s_2\right),...,f_{uk}\left(s_o\right)\right)$$
$$=\left\{\begin{array}{l} 1-\prod_{j=1}^{o}\left(1-i_{fuk(sj)}{}^{\mu(sj)}\right), \\ \prod_{j=1}^{o} n_{fuk(sj)}, \prod_{j=1}^{o}\left(1-i_{fuk(sj)}\right)^{\mu(sj)} \\ -\prod_{j=1}^{o} n_{fuk(sj)}{}^{\mu(sj)} \end{array}\right\}\left(\begin{array}{l} u=1,2,...,v; \\ k=1,2,...,l \end{array}\right) \tag{9}$$

Interval data refers to data represented by upper and lower bounds, suitable for situations where precise values cannot be provided, but a range can be determined. In the environmental impact assessment of GM crops, due to various uncertainties, scientists may only be able to provide a possible range of impact rather than a precise value. For example, the impact of GM crops on soil microbial diversity might only be given as a possible range of change. Specifically, suppose the interval data are represented by $F(s_j)^{\$} = (f_{uk}(s_j))_{v*l}$, where $f_{uk}(s_j) = [x_{fuk}(s_j), y_{fuk}(s_j)]$, the following expression gives the values for the aggregated interval data:

$$\begin{aligned} F_{uk}^{\$} &= \left[x_{fuk}, y_{fuk}\right] \text{ with } x_{fuk} \\ &= MAX\left[x_{fuk}\left(s_j\right)\right], y_{fuk} MIN\left[y_{fuk}\left(s_j\right)\right] \end{aligned} \tag{10}$$

Defining positive and negative ideal points

In the evaluation model based on dynamic mixed multi-attribute decision-making, positive and negative ideal points serve as two critical reference points, representing the optimal and worst promotion schemes, respectively. When assessing the positions of market stakeholders regarding GM crops, positive and negative ideal points need to be defined across different types of data (precise values, intuitionistic fuzzy numbers, and interval numbers).

For precise values, the positive ideal point symbolizes the best performance value on each evaluation attribute, with benefit-type indicators represented by $B_k^{*+} = MAX\{f_{uk}(s_j)\}$ and cost-type indicators by $B_k^{*-} = MAX\{f_{uk}(s_j)\}$. For instance, if the attribute is the yield of GM crops, then the positive ideal point would be the highest yield value in the known data. Conversely, the negative ideal point would be the worst performance value on each attribute. Continuing with the yield example, the negative ideal point would be the lowest yield value, with benefit-type indicators represented by $B_k^{*-} = MAX\{f_{uk}(s_j)\}$ and cost-type indicators by $B_k^{*-} = MAX\{f_{uk}(s_j)\}$.

In the realm of intuitionistic fuzzy numbers, the positive ideal point is characterized by the highest degree of membership, the lowest degree of non-membership, and the lowest degree of hesitation. For example, consumer acceptance of the safety of GM crops could be represented by an intuitionistic fuzzy number with high membership, low non-membership, and low hesitation. The negative ideal point, conversely, represents the lowest degree of membership, the highest degree of non-membership, and the highest degree of hesitation. Assuming the degree to which scheme B_k satisfies attribute H_k in a certain period is denoted by I_{uk}, the maximum value of I_{uk} is determined as the positive ideal solution, i.e., $B_k^{*+} = MAX\{f_{uk}(s_j)\}=MAX\{i_{uk}(s_j)\}$, and the minimum value of I_{uk} as the negative ideal solution, i.e., $B_k^{*-} = MAX\{f_{uk}(s_j)\} = MAX\{i_{uk}(s_j)\}$.

For interval numbers, the positive ideal point is the optimal possible range for that attribute, typically the interval with the highest upper bound. For instance, in environmental impact assessments, the positive ideal point might be the predicted range that minimizes environmental impact. The negative ideal point, then, is the worst possible range, i.e., the interval with the lowest lower bound. In the example of environmental impact, this would be the predicted range with the greatest environmental impact. Specifically, for benefit-type indicators, the positive ideal solution is represented by $B_k^{\$+} = F_{uk}[x_{fuk}^{\$+}, y_{fuk}^{\$+}]$, where $x_{fuk}^{\$+} = MAX\{x_{fuk}(s_j)\}$ and $y_{fuk}^{\$+} = MAX\{y_{fuk}(s_j)\}$, and the negative ideal solution by $B_k^{\$-} = F_{uk}[x_{fuk}^{\$-}, y_{fuk}^{\$-}]$, where $x_{fuk}^{\$+} = MAX\{x_{fuk}(s_j)\}$ and $y_{fuk}^{\$+} =MAX\{y_{fuk}(s_j)\}$. If the indicator is a cost-type, then the positive ideal solution is determined as $B_k^{\$-} = F_{uk}[x_{fuk}^{\$-}, y_{fuk}^{\$-}]$, where $x_{fuk}^{\$+} = MAX\{x_{fuk}(s_j)\}$ and $y_{fuk}^{\$+} = MAX\{y_{fuk}(s_j)\}$, and the negative ideal solution as $B_k^{\$+} = F_{uk}[x_{fuk}^{\$+}, y_{fuk}^{\$+}]$, where $x_{fuk}^{\$+} = MAX\{x_{fuk}(s_j)\}$ and $y_{fuk}^{\$+} = MAX\{y_{fuk}(s_j)\}$.

Combining these three types of indicator data, the intuitionistic fuzzy positive ideal points and negative ideal points for the evaluation model based on dynamic mixed multi-attribute decision-making are represented by $B^+ = (B_1^+, B_2^+, \ldots, B_l^+)^S$ and $B^- = (B_1^-, B_2^-, \ldots, B_l^-)^S$, respectively.

Calculating the distance to positive and negative ideal solutions

Understanding the multi-attribute decision evaluation model for the GM crops market necessitates independently handling three types of data: precise values, intuitionistic fuzzy numbers, and interval numbers, and calculating their proximity to the ideal scenarios. For data represented by precise values, this article compares the actual numerical values of each option against the ideal best or worst numerical values. For instance, the article considers specific yield data for a GM crop and compares it against the highest possible yield in the market. The following formulas provide the calculation of the distance to the positive and negative ideal solutions for each indicator:

$$f(B_k^*, B^+) = |\ B_k^* - B_k^{*+}| = |a_{fuk} - MAX\{f_{uk}(s_j)\} \quad (11)$$

$$f(B_k^*, B^-) = |\ B_k^* - B_k^{*-}| = |a_{fuk} - MIN\{f_{uk}(s_j)\} \quad (12)$$

The distance to the positive and negative ideal solutions for the precise module can be obtained through the following formulas:

$$f(\ B_k^*, B^+\ ) = \sum_{k=1}^{l} \mu_k \left(1 - |\ a_{fuk} - MAX\left\{f_{uk}(s_j)\right\}\right) \quad (13)$$

$$f(\ B_k^*, B^-\ ) = \sum_{k=1}^{l} \mu_k \left(1 - |\ a_{fuk} - MIN\left\{f_{uk}(s_j)\right\}\right) \quad (14)$$

For data represented by intuitionistic fuzzy numbers, which include a degree of uncertainty, this article assesses the match between the possible range of each option and the desired best or worst possible ranges. For example, when considering consumer confidence in the safety of GM foods, there might not be a single specific number but a range of possibilities that require a more complex measurement method. The formulas for calculating the distance to the positive and negative ideal solutions for the intuitionistic fuzzy number module data are provided as follows:

$$f(B_k^{\#}, B^+) = \sum_{k=1}^{l} \mu_k (1 - N_{uk}) \quad (15)$$

$$f(B_k^{\#}, B^-) = \sum_{k=1}^{l} \mu_k (1 + \tau_{uk}) \quad (16)$$

Finally, for data represented by interval numbers, this article examines the range of values provided for each option and evaluates how closely this range approaches the ideal state. The following formulas present the calculation of the distance to the positive and negative ideal solutions for the interval data module:

$$f\left(B_k^{\$}, B^+\right) = \mu_k * \sqrt{\left(x_{uk} - x_{uk}^{\$+}\right)^2 + \left(y_{uk} - y_{uk}^{\$+}\right)^2} \quad (17)$$

$$f\left(B_k^{\$}, B^-\right) = \mu_k * \sqrt{\left(x_{uk} - x_{uk}^{\$-}\right)^2 + \left(y_{uk} - y_{uk}^{\$-}\right)^2} \quad (18)$$

The total distance to the positive and negative ideal solutions for the promotion scheme can be obtained by summing the distances calculated for each module of the constructed model. The promotion scheme with the greatest distance to the positive ideal solution and the smallest distance to the negative ideal solution is identified as the optimal promotion scheme.

$$f(B_k, B^+) = f(B_k^*,B^-) + f(B_k^\#,B^+) + f(B_k^\$,B^+) \tag{19}$$

$$f(B_k, B^-) = f(B_k^*,B^-) + f(B_k^\#,B^-) + f(B_k^\$,B^-) \tag{20}$$

In considering the safety and consumer acceptance of GM crops, this article employs these methods to weigh the advantages and disadvantages of different positions. For example, consumers may prefer products that are closer to the ideal values in safety tests, whereas the market may more strongly support GM crops that show favorable expected ranges in both safety and yield. Through this approach, a comprehensive evaluation can be drawn, indicating which GM crops are likely to achieve higher acceptance in the market and, thereby, have a positive impact on the market.

Experimental Results and Analysis

This study has constructed the fuzzy sample data as shown in Table 1 by fuzzifying the information regarding the safety evaluation of GM crops according to the membership function. Each characteristic in the table has been transformed into fuzzy values to better reflect its relative importance and uncertainty in the safety evaluation.

Further, a set of rule sets was distilled, linking different dimensions of evaluation criteria (biosafety, nutritional value, environmental impact, and socio-economic effects) with evaluation results, and the veracity of each rule, i.e., the rule's confidence level was provided. Rule 1 states: If the biosafety is rated as level A, then regardless of the evaluation in other dimensions, the evaluation result tends to be level A, with a veracity of 100%. Rule 8 indicates: If both biosafety and environmental impact are rated as level C while nutritional value is rated as level A, then the evaluation result tends to be level A, but the veracity of this rule is reduced to 84%. Through such set of rules, it is observed that certain combinations of evaluation indicators, for example, "biosafety level A, nutritional value level D", would lead to an evaluation result tending towards level B, while some directly point to a singular outcome, for example, "biosafety level D, nutritional value level D" would directly result in a level D evaluation result, with the rule's veracity being 100%.

Table 1. Fuzzy sample data.

No.	Category		Biosafety				Nutritional value			
	Gen1	Gen2	A	B	C	D	A	B	C	D
1	1	0	0	0	1	0	0	1	0	0
2	1	0	0	1/6	5/6	0	0	0	0	1
3	1	0	0	0	1	0	1	0	0	0
4	1	0	1	0	0	0	0	0	1	0
5	0	1	1/6	5/6	0	0	0	0	1	0
6	1	0	0	0	1	0	0	1	0	0
7	1	0	0	0	1	0	0	0	1	0
8	0	1	0	0	0	1	1	0	0	0
9	1	0	0	5/6	1/6	0	0	0	1	0
10	0	1	1	0	0	0	0	5/6	1/6	0

No.	Environmental impact				Socio-economic effects				Evaluation results			
	A	B	C	D	A	B	C	D	A	B	C	D
1	1	1/6	5/6	0	0	0	1	0	0	5/6	1/6	0
2	1	0	5/6	1/6	1	0	0	0	0	0	1/6	5/6
3	1	0	1	0	1	0	0	0	1	1	0	0
4	1	1/6	5/6	0	1	0	0	0	0	1	0	0
5	0	0	1/6	5/6	1	0	0	0	0	0	1	0
6	1	0	0	0	1/6	5/6	0	0	0	1	0	0
7	1	0	1	0	1	0	0	0	0	1/6	5/6	0
8	1	0	1	0	1	0	0	0	1	1	0	0
9	1	1/6	5/6	0	1	0	0	0	0	1	0	0
10	0	0	0	0	0	5/6	1/6	0	1	0	0	0

Table 2. Fuzzy decision tree preference matrix.

No.	Biosafety	Nutritional value	Environmental impact	Socio-economic effects	Evaluation result	Veracity
1	A	A	–	–	A	100%
2	A	B	–	–	B	100%
3	A	C	–	–	B	100%
4	A	D	–	–	B	100%
5	B	–	A	–	A	74%
6	B	–	B	–	B	100%
7	B	–	C	–	B	92%
8	C	A	A	–	A	84%
9	C	B	A	–	B	100%
10	C	C	A	–	B	82%
11	C	D	A	–	C	100%
12	C	–	B	–	C	95%
13	C	–	C	–	C	83%
14	C	–	D	–	D	72%
15	D	B	–	–	C	82%
16	D	C	–	–	D	100%
17	D	D	–	–	D	100%

These rule sets, collectively forming a complete fuzzy logic-based decision tree, provide a comprehensive, quantitative decision tool for the safety evaluation of GM crops, taking into account the interaction and uncertainty of different influencing factors. Table 2 presents the preference matrix constructed based on the aforementioned rule set for the fuzzy decision tree.

This paper has developed the following promotion schemes for GM crops to conduct experiments on the market stakeholders' positions assessment based on multi-attribute decision-making. Scheme 1 focuses on education and transparency enhancement strategy, aiming at elevating consumer understanding and transparency regarding genetic modification technology. Through extensive educational activities, such as public lectures, popular science articles, interactive workshops, and the introduction of school curricula, it aims to dispel consumer misconceptions about GM crops. Scheme 2 emphasizes a differentiated market positioning strategy, where market promotion focuses on the specific benefits of GM crops, such as higher yield, improved nutritional value, or stress resistance. By targeting specific market segments, GM crops are positioned to meet special needs. Scheme 3 involves a cooperation and certification strategy, primarily through establishing partnerships with government agencies, non-governmental organizations, industry associations, etc., to enhance consumer trust. Promotion of certified GM food, such as obtaining non-GM project verification or other environmentally and health-related labels, is used to strengthen public confidence in product safety.

The experimental section presented the market stakeholders' position assessment indicator data table for GM crops and conducted a dynamic mixed multi-attribute data normalization, as seen in Tables 3 and 4. The necessity of dynamic mixed multi-attribute data normalization lies in its ability to unify data from different time points and multiple attributes into a common standard framework, ensuring comparability across different times and attributes. This, in turn, makes the assessment results more accurate, consistent, and timely. Such normalization is crucial for reliably tracking and predicting market dynamics, understanding trends in various positions, and formulating corresponding policies or market strategies.

This paper selected two key dimensions, product safety and market share, to calculate their respective distances to the positive and negative ideal solutions. These distances, measured through precise value indicators,

Table 3. Market stakeholders' position assessment indicator data for GM crops.

	Scheme 1	Scheme 2	Scheme 3
Product safety tests	7.8	7.7	7.78
Market share	92%	98%	88%
Consumer trust	Excellent	Excellent	Good
Policy support	Excellent	Excellent	Good
Biodiversity impact evaluation	Very high	Very high	High
Environmental evaluation	0.2–0.5	0.3–0.4	0.1–0.2

Table 4. Normalized data for market stakeholders' position assessment indicators for GM crops.

	Scheme 1	Scheme 2	Scheme 3
Product safety tests	0	0.0125	0.0062
Market share	0.9254	1.0000	0.8785
Consumer trust	(0.84,0.11,0.05)	(0.84,0.11,0.05)	(0.64,0.26,0.11)
Policy support	(0.84,0.11,0.05)	(0.84,0.11,0.05)	(0.64,0.26,0.11)
Biodiversity impact evaluation	(0.84,0.11,0.05)	(0.84,0.11,0.05)	(0.64,0.26,0.11)
Environmental evaluation	0.2–0.5	0.3–0.4	0.1–0.2

reflect the proximity of each stakeholder to the ideal conditions on each indicator. The calculation of the distances to the positive and negative ideal solutions involves quantifying the absolute distance of each indicator to the positive and negative ideal solutions, thereby providing a quantified evaluation indicator for each stakeholder's position. These indicators are further integrated into a comprehensive decision table, which presents the position assessment results of various stakeholders at different time points, as seen in Tables 5–8.

Table 5. Precise value evaluation indicators for the positions of market stakeholders in GM crops with positive and negative ideal solutions.

Indicator	Positive ideal solution	Negative ideal solution
Product safety tests	0.0129	0
Market share	1	0.8785

Table 6. Absolute distance from precise value indicators to the positive ideal solution for the positions of market stakeholders in GM crops.

	Scheme 1	Scheme 2	Scheme 3
Product safety tests	0.0068	0.0068	0.0067
Market share	0.0415	0.0085	0.1125

Table 7. Absolute distance from precise value indicators to the negative ideal solution for the positions of market stakeholders in GM crops.

	Scheme 1	Scheme 2	Scheme 3
Product safety tests	0.0061	0.0063	0.0066
Market share	0.8123	0.1258	0.0152

Table 8. Distance to positive and negative ideal solutions from precise value indicators for the positions of market stakeholders in GM crops.

	Scheme 1	Scheme 2	Scheme 3
Distance to a positive ideal solution	0.0125	0.0043	0.0256
Distance to a negative ideal solution	0.0235	0.0278	0.0058

Furthermore, this paper employed the intuitionistic fuzzy number method to address uncertainty and ambiguity in the decision-making process. Key aspects such as consumer trust, policy support, and biodiversity impact assessment, which often involve subjective judgments and fuzzy information, were selected for the experiment. For each aspect, distances to the positive and negative ideal solutions were calculated. The concepts of positive and negative ideal solutions in the intuitionistic fuzzy environment are used to represent the optimal and least optimal states of decisions. The calculation of distances considers the characteristics of intuitionistic fuzzy numbers, such as degrees of membership and non-membership, offering richer information than traditional fuzzy numbers. By constructing tables of distances to the positive and negative ideal solutions for intuitionistic fuzzy number indicators, it is possible to quantify and assess the positions of stakeholders under different conditions, reflecting the complexity and dynamism of the GM crops market. Specific details are provided in Tables 9 and 10.

Environmental evaluation indicators, often characterized by uncertainty, were addressed using interval-type

Table 9. Intuitionistic fuzzy number evaluation indicators for the positions of market stakeholders in GM crops with positive and negative ideal solutions.

Indicator	Positive ideal solution	Negative ideal solution
Consumer trust	(0.84,0.11,0.05)	(0.51,0.41,0.11)
Policy support	(0.84,0.11,0.05)	(0.64,0.26,0.11)
Biodiversity impact assessment	(0.84,0.11,0.05)	(0.64,0.26,0.11)

Table 10. Distance to positive and negative ideal solutions from intuitionistic fuzzy number indicators for the positions of market stakeholders in GM crops.

	Scheme 1	Scheme 2	Scheme 3
Distance to a positive ideal solution	0.3125	0.3269	0.2896
Distance to a negative ideal solution	0.4215	0.4256	0.4156

indicators to capture this uncertainty. These interval-type indicators not only express the range of indicator values but also reflect the potential fluctuations or uncertainties in evaluation results. To assess different positions, the distance of interval-type indicators to the positive and negative ideal solutions was calculated. The positive ideal solution represents the optimal possible value for each indicator, while the negative ideal solution represents the most adverse scenario. These distances were then used to construct a comprehensive data table, integrating evaluation results from different time points to dynamically present the positions of various stakeholders. Specific details are provided in Tables 11 to 13.

Considering all distances to positive and negative ideal solutions, the comprehensive distances to positive and negative ideal solutions for GM crops market promotion schemes were obtained.

Based on the earlier calculated results, Scheme 2 for the promotion of GM crops exhibits the smallest distance to the positive ideal solution and the largest distance to the negative ideal solution, thus Scheme 2 should be selected as the supplier for the cooperative product in the GM crops market. From the original and comprehensive data tables, it is observed that Scheme 2 for the promotion of GM crops is not the least costly (Table 14). Following the balance principle of stakeholders' positions in the GM crops market, this scheme would necessarily be abandoned in favor of Schemes 1 or 3 for cooperation.

Table 11. Comprehensive data for interval-type indicators for the positions of market stakeholders in GM crops.

	Scheme 1	Scheme 2	Scheme 3
Environmental evaluation	0.2–0.3	0.3–0.4	0.1–0.2

Table 12. Positive and negative ideal solutions for interval-type indicators for the positions of market stakeholders in GM crops.

Indicator	Positive ideal solution	Negative ideal solution
Environmental evaluation	0.3–0.5	0.1–0.2

Table 13. Distance to positive and negative ideal solutions for interval-type indicators for the positions of market stakeholders in GM crops.

	Scheme 1	Scheme 2	Scheme 3
Distance to a positive ideal solution	0.0145	0.0067	0.0238
Distance to a negative ideal solution	0.0094	0.0189	0.0000

Table 14. Comprehensive distances to positive and negative ideal solutions for GM crop market promotion schemes.

	Scheme 1	Scheme 2	Scheme 3
Distance to a positive ideal solution	0.3458	0.3369	0.3389
Distance to a negative ideal solution	0.4369	0.4578	0.4156

However, after considering indicators such as product safety test results, market share, consumer trust survey, policy support, and biodiversity impact assessment comprehensively, this paper concludes that Scheme 2 should be chosen as the final decision for the promotion of GM crops.

Conclusions

The paper initially established a comprehensive safety evaluation indicator system for GM crops, considering consumer acceptance. This system potentially encompasses multiple dimensions, including ecological impact, health risks, economic benefits, and social acceptance, aimed at thoroughly assessing the safety of GM crops. The FuzzyID3 algorithm was utilized for a scientific assessment of the aforementioned system. The FuzzyID3 algorithm, a fuzzy extension of the decision tree algorithm, is capable of handling uncertainty and ambiguity, making it suitable for dealing with imprecise information in evaluation indicators. Innovatively, the paper employed multi-attribute decision theory, forming a dynamic mixed multi-attribute decision model for assessing the positions of various market stakeholders concerning GM crops through dynamic data integration. This involved calculating the distances to ideal solutions for each module and applying weighting to reflect the dynamic changes over time in stakeholders' positions.

This research fills the existing gap in the safety evaluation of GM crops, especially from the perspective of consumer acceptance, providing a scientific assessment tool and decision support for the market promotion and policy formulation of GM crops. The innovative application of the dynamic mixed multi-attribute decision model enhances the flexibility and adaptability of the evaluation process, enabling the assessment to reflect real-time changes in market and societal attitudes.

Although the paper has made significant progress in the safety evaluation and market decision-making of GM crops, this research has some limitations. First, data collection in the field of GM crops may be limited by issues of data reliability and coverage. Some data may be constrained by the methods of data collection or the limitations of data sources, affecting the integrity and accuracy of the evaluation indicator system. Second, the complexity of methods such as the FuzzyID3 algorithm and multi-attribute decision models may lead to insufficient interpretability of their results. Complex models may make it difficult to clearly explain the decision-making logic behind them, limiting the understanding and acceptance of the results by decision-makers and stakeholders. Considering these limitations, future research could further optimize data collection methods, model construction techniques, and the result interpretation frameworks to enhance the scientific rigor and practicality of research in the field of GM crops.

Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

Abikenova, S., Issamadiyeva, G., Kulmagambetova, E., Daumova, G. and Abdrakhmanova, N. 2023. Assessing occupational risk: A classification of harmful factors in the production environment and labor process. International Journal of Safety and Security Engineering 13(5): 871–881. https://doi.org/10.18280/ijsse.130511

Akinbo, O., Hancock, J. F. and Makinde, D. 2015. Relevance of crop biology for environmental risk assessment of GM crops in Africa. Frontiers in Bioengineering and Biotechnology 3: 150. https://doi.org/10.3389/fbioe.2015.00150

Bundschuh, R., Kuhn, U., Bundschuh, M., Naegele, C., Elsaesser, D., Schlechtriemen, U., et al. 2016. Prioritizing stream types according to their potential risk to receive crop plant material – A GIS-based procedure to assist in the risk assessment of GM crops and systemic insecticide residues. Science of the Total Environment 547: 226–233. https://doi.org/10.1016/j.scitotenv.2015.12.124

Dolezel, M., Miklau, M., Heissenberger, A. and Otto, M. 2024. Agronomic and phenotypic plant traits as indicators for environmental risks of GM plants. Environmental Sciences Europe 36(1): 1–20. https://doi.org/10.1186/s12302-023-00828-y

Dwijendra, N. K. A., Saptaningtyas, R. S., Mahendra, S. J., Huamán-Romaní, Y. L., Seminario-Morales, M. V., Sánchez-Prieto, M. G., et al. 2023. Optimizing energy consumption in legume production to mitigate greenhouse gas emissions: An empirical investigation. Mathematical Modelling of Engineering Problems, 10(5): 1901–1906. https://doi.org/10.18280/mmep.100544

Espolov, T., Espolov, A., Satanbekov, N., Tireuov, K., Mukash, J. and Suleimenov, Z. 2023. Economic trend in developing sustainable agriculture and organic farming. International Journal of Sustainable Development and Planning, 18(6): 1885–1891. https://doi.org/10.18280/ijsdp.180624

Fedorova, M. and Herman, R. A. 2020. Obligatory metabolomic profiling of gene-edited crops is risk disproportionate. The Plant Journal 103(6): 1985–1988. https://doi.org/10.1111/tpj.14896

Haselmair-Gosch, C., Nitarska, D., Walliser, B., Flachowsky, H., Marinovic, S. and Halbwirth, H. 2020. Event-specific qualitative polymerase chain reaction analysis for two T-DNA copies in GM orange Petunia. Plant Cell, Tissue and Organ Culture 142(2): 415–424. https://doi.org/10.1007/s11240-020-01871-w

Kamthan, A., Chaudhuri, A., Kamthan, M. and Datta, A. 2016. Genetically modified (GM) crops: Milestones and new advances in crop improvement. Theoretical and Applied Genetics 129: 1639–1655. https://doi.org/10.1007/s00122-016-2747-6

Koch, M., DeSesso, J., Williams, A., Michalek, S. and Hammond, B. 2016. Adaptation of the ToxRTool to assess the reliability of toxicology studies conducted with GM crops and implications for future safety testing. Critical Reviews in Food Science and Nutrition 56(3): 512–526. https://doi.org/10.1080/10408398.2013.788994

Krizkovska, B., Viktorova, J. and Lipov, J. 2022. Approved genetically modified potatoes (Solanum tuberosum) for improved stress resistance and food safety. Journal of Agricultural and Food Chemistry 70(38): 11833–11843. https://doi.org/10.1021/acs.jafc.2c03837

Liu, T. 2020. The European Union's experience in prudential supervision over GM foods and its enlightenment for China. Food Science 41(5): 282–289. https://www.spkx.net.cn/EN/10.7506/spkx1002-6630-20190409-113

Muthu, S. P. V. and Devadoss, A. K. V. 2023. Genetically optimized neural network for early detection of glaucoma and cardiovascular disease risk prediction. Traitement du Signal 40(4): 1641–1651. https://doi.org/10.18280/ts.400432

Olabinjo, O. O., Okunola, A. A. and Olumurewa, J. A. V. 2020. GM foods: Pathway to food security. IOP Conference Series: Earth and Environmental Science 445(1): 012041. https://doi.org/10.1088/1755-1315/445/1/012041

Oliver, D. P., Kookana, R. S., Miller, R. B. and Correll, R. L. 2016. Comparative environmental impact assessment of herbicides used on GM and non-GM herbicide-tolerant canola crops using two risk indicators. Science of the Total Environment 557–558: 754–763. https://doi.org/10.1016/j.scitotenv.2016.03.106

Oshergina, I. and Ten, E. 2023. Harnessing heterogeneity: Clustering Kazakh spring rapeseed for breeding value. International Journal of Design & Nature and Ecodynamics 18(5): 1087–1095. https://doi.org/10.18280/ijdne.180509

Pataer, P., Gao, K., Zhang, P. and Li, Z. 2024a. Ultrasensitive and visual detection of GM crops using two primers-induced cascade exponential amplification assay. Talanta 268: 125282. https://doi.org/10.1016/j.talanta.2023.125282

Pataer, P., Gao, K., Zhang, P., Wang, X. and Li, Z. 2024b. A simple, portable and multiplex LAMP-based CRISPR/Cas12a assay for visually screening GM crops. Sensors and Actuators B: Chemical 403: 135124. https://doi.org/10.1016/j.snb.2023.135124

Paul, T. K., Jana, C. and Pal, M. 2023. Enhancing multi-attribute decision making with Pythagorean Fuzzy Hamacher Aggregation Operators. Journal of Industrial Intelligence 1(1): 30–54. https://doi.org/10.56578/jii010103

Raybould, A. and Macdonald, P. 2018. Policy-led comparative environmental risk assessment of GM crops: Testing for increased risk rather than profiling phenotypes leads to predictable and transparent decision-making. Frontiers in Bioengineering and Biotechnology 6: 43. https://doi.org/10.3389/fbioe.2018.00043

Safaei, P., Rezaie, S., Alimohammadi, M., Agha Kuchak Afshari, S., Mehdizadeh, M. and Molaee Aghaee, E. 2020. Qualitative PCR-based detection of genetically modified soy and maize products in Iran. International Journal of Food Properties 23(1): 459–469. https://doi.org/10.1080/10942912.2020.1734613

Shin, M., Jeon, S. and Koo, Y. 2022. Development of a rapid detection method for GM rice using the ultra-fast PCR system. Food Science and Biotechnology 31(2): 175–182. https://doi.org/10.1007/s10068-021-01025-4

Shin, M., Jeon, S. and Koo, Y. 2023. Detection method for GM potato using an ultra-fast PCR system. Food Science and Biotechnology 32(9): 1185–1191. https://doi.org/10.1007/s10068-023-01258-5

Sonhaji, Wibawa, K. C. S., Natalis, A. and Noho, M. D. H. 2022. Animal rights in Indonesian Environmental Law: Case studies in disaster-prone areas. International Journal of Sustainable Development and Planning 17(1): 299–305. https://doi.org/10.18280/ijsdp.170130

Suh, S., Kim, H., Shin, M., Hong, S., Cha, J. and Kim, H. 2024. Multiplex PCR detection method of GM canola event (MON94100, LBFLFK, and NS-B50027-4) combined with capillary electrophoresis. Food Science and Biotechnology 33(3): 637–643. https://doi.org/10.1007/s10068-023-01377-z