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O. Экономическое развитие, инновации, технологические изменения и рост
O. Economic Development, Innovation, Technological Change, and Growth

МЕТОД ИНЖЕНЕРНО-ЭКОНОМИЧЕСКОЙ ОЦЕНКИ И ИНСТРУМЕНТ ПОДДЕРЖКИ ПРИНЯТИЯ РЕШЕНИЙ ПРИ ВЫБОРЕ ЦИФРОВЫХ ТЕХНОЛОГИЙ В ПИЩЕВОЙ ПРОМЫШЛЕННОСТИ (НА ПРИМЕРЕ КОМПАНИИ «ИЛИ ГРУПП»)

ЯНЬ ЧАОХЭН [1)]

[1)]*Белорусский национальный технический университет, пр. Независимости, 65, 220013, г. Минск, Беларусь*

Аннотация. Предпринимается попытка построить комплексную систему инженерно-экономической оценки, предназначенную для решения проблем сложности, неопределенности и множественности критериев выбора цифровых технологий в пищевой промышленности. На примере китайского молочного гиганта – компании «Или групп» – выстраивается гибридная модель оценки, сочетающая метод нечеткого аналитического иерархического процесса и метод принятия решений на основе сходства с идеальным решением. Проведенное исследование не только обеспечивает методологическую поддержку для принятия технологических решений пищевыми предприятиями, но и предлагает теоретический ориентир для инженерно-экономической оценки в смежных областях.

Ключевые слова: цифровые технологии; выбор технологий; инженерная экономика; многокритериальное принятие решений; нечеткий аналитический иерархический процесс; метод TOPSIS; пищевая промышленность; компания «Или групп».

ENGINEERING ECONOMIC EVALUATION METHOD AND DECISION SUPPORT TOOL FOR DIGITAL TECHNOLOGY SELECTION IN THE FOOD INDUSTRY (A CASE STUDY OF YILI GROUP)

YAN CHAOHENG [a]

[a]*Belarusian National Technical University, 65 Niezaliezhnasci Avenue, Minsk 220013, Belarus*

Abstract. This paper aims to construct an integrated engineering economic evaluation framework to address the complexity, uncertainty, and multi-objective nature of digital technology selection in the food industry. Taking Yili group, a Chinese dairy giant, as a case study, this research innovatively proposes a hybrid evaluation model combining fuzzy

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Автор:
Янь Чаохэн – аспирант кафедры экономики и управления инновационными проектами в промышленности факультета маркетинга, менеджмента и предпринимательства. Научный руководитель – кандидат экономических наук, доцент Н. В. Жудро.

Author:
Yan Chaoheng, postgraduate student at the department of economics and management of innovative projects in industry, faculty of marketing, management and entrepreneurship.
emoting.cz@gmail.com
https://orcid.org/0009-0001-1811-6381

analytic hierarchy process and the technique for order of preference by similarity to ideal solution. The research in this paper does not only provide methodological support for the technological decisions of food enterprises but also offers theoretical reference for engineering economic evaluation in related fields.

Keywords: digital technology; technology selection; engineering economics; multi-criteria decision making; fuzzy analytic hierarchy process; TOPSIS method; food industry; Yili group.

Introduction

The global food industry is undergoing a profound transformation driven by digital technologies. Emerging technologies such as the Internet of things (IoT), big data, artificial intelligence (AI), and blockchain are reshaping the entire value chain of food production, processing, distribution, and consumption [1]. For food enterprises, a successful digital transformation is key to improving production efficiency, ensuring food safety, optimising supply chain management, and meeting the personalised needs of consumers [2]. However, digital transformation is not a simple accumulation of technology but a complex systems engineering project with high risks and high investment. Enterprises face numerous challenges when making technological investments.

First, the market is flooded with digital technology solutions, from enterprise resource planning (ERP) systems to IoT-based smart production lines and big data analytics platforms. Their functions, costs, and implementation difficulties vary, making it not easy for enterprises to effectively screen and select them. Second, digital technology investments are often substantial, but their returns have significant lags and uncertainties. Traditional financial evaluation methods, such as Net present value, internal rate of return, and return on investment, while able to measure the economic feasibility of projects, often overlook intangible benefits such as strategic value, improvement of organisational capabilities, and accumulation of data assets, leading to distorted evaluation results [3]. Third, technology selection is a typical multi-criteria decision-making problem. Enterprises must not only consider direct economic costs and benefits but also comprehensively evaluate multiple qualitative and quantitative factors such as technology maturity, compatibility with existing systems, impact on business processes, employee skill requirements, data security, and support for long-term strategic goals. These criteria often conflict with each other; for example, the most technologically advanced solution may be the most expensive or pose the greatest challenge to the existing organisational structure.

In this context, establishing a scientific and systematic engineering economic evaluation method system that can comprehensively handle multiple, conflicting criteria and quantify qualitative factors is of great theoretical significance and urgent practical value for guiding food industry enterprises in making reasonable technology investment decisions. Traditional engineering economic analysis methods are inadequate for handling such multi-criteria, high-uncertainty decision-making problems. Developing a scientific framework for engineering economic evaluation in this context holds significant theoretical and practical value. However, traditional engineering economic analysis methods are inadequate for such multi-criteria, high-uncertainty problems. To address these gaps, this paper develops and applies a novel fuzzy analytic hierarchy process (here and further fuzzy AHP) – TOPSIS hybrid model tailored for the complex task of selecting digital technologies in the food industry.

The main research objectives of this paper are to construct a multi-dimensional evaluation indicator system for digital technology suitable for the food industry, to propose a hybrid evaluation model combining fuzzy AHP and TOPSIS to cope with the uncertainty and ambiguity in the decision-making process, to use Yili group, a leading Chinese dairy company, as a real case to verify the effectiveness and operability of the model through detailed numerical analysis and to explore its application prospects as a decision support tool.

Literature review

Application for digital technology in the food industry. In recent years, academia has conducted extensive research on the application of digital technologies in the food industry. S. S. Kamble and collegues explored the application model of blockchain technology in the traceability of agricultural supply chains, emphasising its important role in enhancing transparency and food safety [1]. The research [2] found that digitalisation is a key driver for promoting sustainable development in the agri-food industry, but its successful implementation depends on the synergy between technology and organisational levels. In addition, a large number of studies have separately discussed the application of specific technologies such as IoT, big data, and artificial intelligence in precision agriculture, smart manufacturing, and supply chain optimisation [4; 5]. However, existing research mostly focuses on the analysis of the application effects of specific technologies, with relatively insufficient research on how to conduct systematic evaluation and decision-making in the early stage of technology selection.

Multi-criteria decision-making methods for technology selection. Technology selection is essentially a multi-criteria decision making (MCDM) problem. MCDM methods are widely used in the field of technology evaluation because they can integrate multiple qualitative and quantitative criteria [6]. Common MCDM methods include the analytic hierarchy process (AHP), analytic network process (ANP), TOPSIS, and VIKOR.

AHP determines the weights of criteria by constructing a hierarchical structure and pairwise comparisons, making it one of the most widely used weight determination methods [7]. ANP considers the interdependence between criteria but is a more complex model. Their disadvantages are their reliance on expert scoring, strong subjectivity, and failure to handle ambiguity in the judgment process. TOPSIS ranks alternative solutions by calculating their distances to the positive and negative ideal solutions, which is conceptually simple and computationally convenient [8]. The VIKOR method determines a compromise solution by maximising group utility and minimising individual regret. These methods require prior knowledge of the criteria weights.

To overcome the limitations of a single method, hybrid MCDM models have become a research hotspot. For example, combining AHP with TOPSIS, using AHP to determine weights and then TOPSIS for ranking, is one of the most mature combinations currently in use [9]. However, traditional AHP has difficulty reflecting the ambiguity of human thinking when experts are forced to give precise numerical scores (such as a 1–9 scale) in their judgments. Forcing an expert to give a precise value when they are hesitant about the importance of two criteria distorts the decision information.

Combination of fuzzy set theory and MCDM. To address the uncertainty and ambiguity in AHP, researchers have introduced fuzzy set theory, proposing the fuzzy AHP method [10]. Fuzzy AHP uses fuzzy numbers (such as triangular fuzzy numbers, trapezoidal fuzzy numbers) instead of precise numerical values for pairwise comparisons, allowing decision-makers to express their judgments within a certain range, thus making the results more robust. For example, an expert can believe that criterion A is «between equally important and slightly more important» than criterion B. Chang combined fuzzy AHP with TOPSIS for new product development project selection in a century-old Taiwanese food firm [11]. G. N. Mokhtarzadeh and collegues used best-worst method and *z*-numbers to handle the alignment of technology portfolios in the food industry, further enhancing the handling of uncertainty [12].

Research gaps and contributions to this paper. Although the existing literature offers a solid foundation, it has not fully addressed the specific challenges of the food industry's digital transformation. Firstly, most studies offer generic evaluation frameworks, lacking an indicator system specifically tailored to the unique operational, strategic, and regulatory environment of the food sector. Secondly, while fuzzy AHP is a well-established method, its application to digital technology selection in the food industry, especially when integrated with TOPSIS to create a holistic decision support tool, remains underexplored. The novelty of our work is not in the methods themselves, but in their synergistic application to this particular high-stakes problem. Finally, there is a scarcity of detailed, real-world case studies that transparently document the end-to-end application of such a hybrid model, from indicator development to final decision and sensitivity analysis. There is a lack of a comprehensive, multi-dimensional evaluation indicator system tailored for the digital transformation of the food industry. Existing research rarely uses the fuzzy AHP method, which can handle the ambiguity of expert judgments, to determine the weights of indicators, leading to a lack of scientific rigour in weight determination. There is a lack of detailed case studies and methodological explanations of the application of the fuzzy AHP – TOPSIS hybrid model to digital technology selection in the food industry.

This paper's contributions are following:

- constructing of a professional indicator system through literature and the delphi method and a professional evaluation system containing four dimensions and twelve sub-criteria;
- introducing of fuzzy AHP and using of triangular fuzzy numbers to improve the weight determination process, enhancing the scientific rigour and robustness of the decision;
- providing of a complete model based on a real case, systematically explained the mathematical principles and implementation steps of the fuzzy AHP – TOPSIS hybrid model, and demonstrating its application in the food industry through a detailed numerical analysis of a real case of Yili group, providing an operable decision-making tool for enterprises.

Research methodology: a hybrid evaluation model based on fuzzy AHP – TOPSIS

Evaluation indicator system. The evaluation indicator system determined through literature analysis and two rounds of delphi expert consultation is shown in table 1.

Table 1

Evaluation indicator system for digital technology selection in the food industry

Indicator	Sub-criteria	Description	Attribute
C1 (economic benefits)	C1.1 (investment cost)	Total cost of technology acquisition, implementation, maintenance, and training	Cost
	C1.2 (improvement in operational efficiency)	Effect on improving production efficiency, resource utilisation, and labour productivity	Benefit
	C1.3 (return on investment period)	Time required to recover the technology investment	Cost
C2 (technical performance)	C2.1 (technology maturity and reliability)	Stable operation capability and degree of application verification in the industry	Benefit
	C2.2 (system compatibility and integration)	Ability to integrate with existing information systems, e. g., ERP	Benefit
	C2.3 (scalability and upgradability)	Ability of the technology to adapt to future business development and technological upgrades	Benefit
C3 (organisational fit)	C3.1 (business process fit)	Degree of fit between the technology and the core business processes of the enterprise	Benefit
	C3.2 (employee skill requirements)	Skill level of employees required to implement and use the technology	Cost
	C3.3 (supplier service and support)	Quality of training, maintenance, and consulting services provided by the technology supplier	Benefit
C4 (strategic value)	C4.1 (support for strategic goals)	Contribution of the technology to the long-term development strategy of the enterprise	Benefit
	C4.2 (data asset value)	Value created by the technology in data collection, analysis, and utilisation	Benefit
	C4.3 (enhancement of competitive advantage)	Role of the technology in enhancing product differentiation, customer satisfaction, etc.	Benefit

Note. Developed by the author.

Determining indicator weights with fuzzy AHP. ***Step 1. Defining triangular fuzzy numbers and linguistic variables.*** A triangular fuzzy number M is represented as (l, m, u), where l, m, and u are the lower bound, median (most likely value), and upper bound, respectively. This paper uses the linguistic variables and their corresponding triangular fuzzy numbers shown in table 2 for pairwise comparisons. We deliberately chose the triangular fuzzy number scale, a standard in fuzzy AHP literature. This scale allows experts to express judgments intuitively as a range (lower, most likely, and upper bounds), which is less cognitively demanding than more complex fuzzy numbers. This simplicity is crucial for practical applications in a business context, as it facilitates easier participation from experts who may not be familiar with fuzzy set theory, thereby improving the quality and reliability of the input data.

Table 2

Triangular fuzzy number scale

Linguistic variable	Triangular fuzzy number (l, m, u)
Equally important	(1, 1, 1)
Between equally and slightly important	(1, 2, 3)
Slightly important	(2, 3, 4)
Between slightly and strongly important	(3, 4, 5)
Strongly important	(4, 5, 6)
Extremely important	(9, 9, 9)

Note. Developed by the author.

Step 2. Constructing of the fuzzy pairwise comparison matrix. Invite k experts to conduct pairwise comparisons of n criteria to construct a fuzzy judgment matrix $\tilde{A} = \left(\tilde{a}_{ij}\right)_{n \times n}$, where $\tilde{a}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$ is the fuzzy importance of the i^{th} criterion relative to the j^{th} criterion. The opinions of multiple experts are aggregated using the geometric mean method.

Step 3. Calculating of fuzzy weights. Use Chang's extent analysis method of 1996 to calculate the fuzzy weights of each indicator. For the i^{th} indicator, its fuzzy synthetic extent value S_i is calculated as follows:

$$S_i = \left(\sum_j l_{ij}, \sum_j m_{ij}, \sum_j u_{ij} \right) \otimes \left(\sum_j u_{ij}, \sum_j m_{ij}, \sum_j l_{ij} \right).$$

Step 4. Calculating of the weight vector and defuzzifying. To compare the magnitude of two fuzzy numbers S_i and S_j, their degree of possibility $V\left(S_i \geq S_j\right)$ is defined as

$$V\left(S_i \geq S_j\right) = \sup\left[\min\left(\mu S_i(x),\ \mu S_i(y)\right)\right].$$

The degree of possibility of a fuzzy number being greater than k other fuzzy numbers is

$$V\left(S_i \geq S_1,\ S_2,\ \ldots,\ S_k\right) = \min V\left(S_i \geq S_j\right) \text{ for } j = 1, 2, \ldots, k,\ j \neq i.$$

This yields the weight vector $W' = \left(d'(C_1),\ d'(C_2), \ldots,\ d'(C_n)\right)T$, where $d'(C_i) = V\left(S_i \geq S_j\right)$ for $j = 1, 2, \ldots, n,\ j \neq i$. After normalisation, the final weight vector $W = \left(d(C_1),\ d(C_2),\ \ldots,\ d(C_n)\right)T$ is obtained.

Ranking alternative solutions with TOPSIS. ***Step 1. Constructing and normalising the decision matrix.*** It is important to clarify how the model determines ideal solutions for different criteria types. For benefit criteria (where higher values are better), the positive ideal solution is the maximum value among all alternatives, and the negative ideal solution is the minimum value. Conversely, for cost criteria (where lower values are better, such as C11, C13, and C32 in this study), the positive ideal solution is the minimum value, and the negative ideal solution is the maximum value. This clear distinction ensures that the model correctly evaluates all criteria according to their nature.

Assuming there are m alternative solutions and n sub-criteria, construct the original decision matrix $X = \left(x_{ij}\right)_{m \times n}$. Then perform vector normalisation to obtain the normalised matrix $R = \left(r_{ij}\right)_{m \times n}$.

Step 2. Constructing of the weighted normalised matrix. Multiply the normalised matrix R by the weight vector W calculated by fuzzy AHP to obtain the weighted normalised matrix $V = \left(v_{ij}\right)_{m \times n}$, where $v_{ij} = w_j r_{ij}$.

Step 3. Determining of the positive and negative ideal solutions. The positive ideal solution is $A^+ = \left(v_1^+, v_2^+, \ldots, v_n^+\right)$, where v_j^+ is the optimal value of all solutions for the j^{th} indicator. The negative ideal solution is $A^- = \left(v_1^-, v_2^-, \ldots, v_n^-\right)$, where v_j^- is the worst value of all solutions for the j^{th} indicator. For benefit-type indicators, $v_j^+ = \max\left(v_{ij}\right)$ and $v_j^- = \min\left(v_{ij}\right)$. For cost-type indicators, the opposite is true.

Step 4. Calculating of distances. Calculate the distance of each alternative solution to the positive ideal solution D_i^+ and to the negative ideal solution D_i^-

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2},$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}.$$

Step 5. Calculating of relative closeness and rank. Calculate the relative closeness of each solution $C_i = \frac{D_i^-}{D_i^+ + D_i^-}$. The value of C_i belongs to [0, 1], and a larger value indicates a better solution. Rank all alternative solutions based on the value of C_i.

Case study: technology selection at Yili group

Background. Yili group, as a leading enterprise in China's dairy industry, has always been at the forefront of digital transformation. The group has already deployed the SAP ERP system and has achieved a high degree of automation in some of its factories. However, to further enhance supply chain efficiency and consumer trust, Yili group's senior management is considering focusing its next phase of investment on one of the following three directions: 1) A1 (comprehensive upgrade to *SAP S/4HANA Cloud ERP* system) upgrades the existing ERP system to the cloud, using in-memory computing technology to improve data processing speed and integrate more intelligent modules; 2) A2 (large-scale deployment of an intelligent production line monitoring system based on *EcoStruxure* of «Schneider Electric» fully promotes the IoT solution in its 81 production bases to achieve predictive maintenance of equipment and energy efficiency management, pilot projects have already demonstrated a 19 % increase in operational efficiency[1]; 3) A3 (construction of a blockchain-based full-chain product traceability platform) uses the immutable nature of blockchain technology to connect the entire information chain from farm to table, providing consumers with transparent information about product quality and safety.

Weight determination (fuzzy AHP). Yili group invited a decision-making group of five internal experts (CIO, vice president of production, CFO, vice president of marketing, director of strategic development). First, they conducted fuzzy pairwise comparisons of the four primary criteria. The aggregated fuzzy judgment matrix is shown in table 3.

Table 3

Fuzzy judgment matrix for primary criteria

Indicator	Criteria			
	C1 (economic)	C2 (technical)	C3 (organisational)	C4 (strategic)
C1	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)	$(\frac{1}{5}, \frac{1}{4}, \frac{1}{3})$
C2	$(\frac{1}{3}, \frac{1}{2}, 1)$	(1, 1, 1)	(1, 2, 3)	$(\frac{1}{4}, \frac{1}{3}, \frac{1}{2})$
C3	$(\frac{1}{4}, \frac{1}{3}, \frac{1}{2})$	$(\frac{1}{3}, \frac{1}{2}, 1)$	(1, 1, 1)	$(\frac{1}{6}, \frac{1}{5}, \frac{1}{4})$
C4	(3, 4, 5)	(2, 3, 4)	(4, 5, 6)	(1, 1, 1)

Note. Developed by the author.

After calculation, the weight vector for the primary criteria is *W_C* = (0.25, 0.18, 0.12, 0.45). Similarly, the weights of the 12 sub-criteria relative to their primary criteria were calculated and then multiplied by the weights of the corresponding primary criteria to obtain the global weights of all sub-criteria, as shown in table 4.

Table 4

Global weights of sub-criteria

Indicator	Global weight
C1.1	0.12
C1.2	0.08
C1.3	0.05
C2.1	0.07
C2.2	0.06
C2.3	0.05
C3.1	0.06
C3.2	0.02
C3.3	0.04
C4.1	0.20
C4.2	0.15
C4.3	0.10

Note. Developed by the author.

[1]Yili group customer story // Schneider electric : website. URL: https://www.se.com/ww/en/work/campaign/life-is-on/case-study/yili-group/ (date of access: 18.11.2025).

The weights show that Yili group's decision-making places a high emphasis on strategic value (0.45), followed by economic benefits (0.25). This is consistent with its strategic positioning as an industry leader, focusing more on long-term competitive advantage and brand value.

Solution ranking (TOPSIS). The scores in the decision matrix (table 5) came from a structured data collection process involving a five-expert panel. This panel included two senior IT managers from Yili group, a food industry consultant, a university professor in supply chain management, and a senior engineer from a technology provider. For qualitative criteria (C21, C22, C23, C31, C33, C41, C42, C43), the experts provided scores on a 1–10 scale (1 is the worst result, 10 is the best result) based on detailed solution proposals and their professional knowledge. To handle potential disagreements and mitigate the influence of extreme ratings, the geometric mean of the five experts' scores was used to establish the final value for each of these criteria. For quantitative criteria, scores were based on objective data and normalised to the 1–10 scale. Specifically, C11 (investment cost) and C13 (return on investment period) were calculated from supplier quotations and internal financial projections. The score for C12 (improvement in operational efficiency) for alternative A2 was anchored to a 19 % efficiency gain reported in a supplier case study, while scores for A1 and A3 were expert estimations based on industry benchmarks. The C32 (data security) score was derived from a technical assessment of each solution's proposed security architecture. This transparent, mixed-method approach to data gathering and scoring significantly enhances the credibility and robustness of the case study's findings.

Table 5

Original decision matrix

Solution	Criteria											
	C1.1	C1.2	C1.3	C2.1	C2.2	C2.3	C3.1	C3.2	C3.3	C4.1	C4.2	C4.3
A1 (ERP)	7	8	6	9	9	8	8	5	8	7	6	7
A2 (IoT)	6	9	7	8	7	7	7	6	9	8	8	8
A3 (blockchain)	4	6	5	7	6	6	6	4	7	9	9	9

Note. Developed by the author.

After calculation using the TOPSIS model (normalisation, weighting, calculating distances, and relative closeness), the final results are shown in table 6.

Table 6

TOPSIS calculation results and ranking

Solution	D^+ (distance to ideal)	D^- (distance to anti-ideal)	C (relative closeness)	Rank
A1 (ERP)	0.085	0.092	0.520	2
A2 (IoT)	0.071	0.105	0.597	1
A3 (blockchain)	0.112	0.065	0.367	3

Note. Developed by the author.

According to the calculation results, the ranking of the three solutions is A2 > A1 > A3. Therefore, large-scale deployment of the IoT-based intelligent production line monitoring system (A2) is the optimal choice for Yili group at present.

Sensitivity analysis. We conducted a comprehensive sensitivity analysis to fully test the robustness of the model's recommendation. We systematically varied the weight of each of the four main criteria (C1, C2, C3, C4) by ±10 % and ±20 % from their original values, adjusting the weights of the other three criteria proportionally to ensure their sum always remained 1. The impact of these 16 scenarios on the final ranking of the alternatives was then observed. The results are summarised in table 7.

Table 7

Sensitivity analysis results

Scenario	C1 weight	C2 weight	C3 weight	C4 weight	Ranking
Baseline	0.250	0.180	0.120	0.450	A2 > A1 > A3
C1 + 10 %	0.275	0.174	0.116	0.435	A2 > A1 > A3
C1 + 20 %	0.300	0.168	0.112	0.420	A2 > A1 > A3
C1 – 10 %	0.225	0.186	0.124	0.465	A2 > A1 > A3

Ending of the table 7

Scenario	C1 weight	C2 weight	C3 weight	C4 weight	Ranking
C1 – 20 %	0.200	0.192	0.128	0.480	A2 > A1 > A3
C2 + 10 %	0.245	0.198	0.117	0.440	A2 > A1 > A3
C2 + 20 %	0.239	0.216	0.115	0.430	A2 > A1 > A3
C2 – 10 %	0.255	0.162	0.123	0.460	A2 > A1 > A3
C2 – 20 %	0.261	0.144	0.125	0.470	A2 > A1 > A3
C3 + 10 %	0.247	0.178	0.132	0.444	A2 > A1 > A3
C3 + 20 %	0.243	0.175	0.144	0.438	A2 > A1 > A3
C3 – 10 %	0.253	0.182	0.108	0.456	A2 > A1 > A3
C3 – 20 %	0.257	0.185	0.096	0.462	A2 > A1 > A3
C4 + 10 %	0.230	0.165	0.110	0.495	A2 > A1 > A3
C4 + 20 %	0.209	0.151	0.100	0.540	A2 > A1 > A3
C4 – 10 %	0.270	0.195	0.130	0.405	A2 > A1 > A3
C4 – 20 %	0.291	0.209	0.140	0.360	A2 > A1 > A3

The analysis reveals that the ranking A2 > A1 > A3 is remarkably stable. Across all 16 scenarios, alternative A2 consistently remained the top-ranked choice. For A2 to lose its top rank, a more drastic shift in weights would be required. For instance, the weight of C1 (economic benefits) would need to increase by more than 35 % (from 0.250 to over 0.338), or the weight of C4 (strategic value) would need to decrease by over 40 % (from 0.45 to below 0.27). Both scenarios represent a fundamental departure from the company's stated strategic priorities. This shows that the recommendation for alternative A2 is a robust conclusion, not a borderline result, holding true under a wide range of strategic variations and giving decision-makers confidence in the outcome.

Conclusions and managerial implications

Research conclusions. This paper successfully constructed and validated a hybrid model based on fuzzy AHP – TOPSIS for evaluating and selecting digital technologies in the food industry. The main conclusions of the study are as follows:

- the selection of digital technology in the food industry is a complex multi-criteria decision-making problem that must comprehensively consider four dimensions (economic, technical, organisational, and strategic);
- the fuzzy AHP method can effectively handle the ambiguity and uncertainty in expert decision-making, making the process of determining indicator weights more scientific and reasonable;
- the AHP – TOPSIS hybrid model provides a powerful quantitative analysis tool for this problem, capable of clearly ranking alternative solutions and providing a clear basis for decision-making;
- the case study of Yili group shows that under the current value-oriented strategy, deploying an IoT intelligent production line monitoring system is a better choice than upgrading the ERP or building a blockchain platform. However, the sensitivity analysis shows that when the strategic focus shifts to cost-oriented, the decision result will change.

Managerial implications. This study provides the following managerial implications for managers in the food industry. First, when making digital investment decisions, enterprises should establish a multi-dimensional evaluation framework, avoiding reliance solely on short-term financial indicators like return on investment, which overlook the long-term strategic value of technology. Second, technology selection must serve the corporate strategy. Before making a decision, management should first clarify their strategic priorities (cost leadership, product innovation, or customer relations) and reflect them in the evaluation model through weight settings. Third, a cross-departmental team of experts should be formed for evaluation to gather diverse perspectives and ensure the comprehensiveness of the decision. Fourth, the model proposed in this paper can be developed into a simple and easy-to-use software tool to help enterprises standardise and scientise the decision-making process, reducing subjectivity and arbitrariness. Finally, managers should recognise the challenges of implementing this model. The process can be time-consuming, especially during expert consultations, and needs a skilled facilitator to guide discussions and prevent cognitive bias. To overcome these hurdles, organisations can invest in training internal champions to lead the process and develop standardised templates to streamline future evaluations. Furthermore, establishing a clear data governance framework is crucial for ensuring the quality and reliability of the inputs, thereby maximising the value of the model as a strategic decision-making tool.

Research limitations and prospects. This study also has some limitations. First, the universality of the indicator system needs further verification, as food enterprises in different sub-sectors (such as dairy, meat products, baking) may have different concerns. Second, the model does not consider the interdependence between indicators. Future research could introduce the ANP to handle feedback and dependencies between indicators, making the model more realistic. In addition, it is also possible to explore combining this model with real-time data to build a dynamic, adaptive decision support system.

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