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DETERMINING THE PROSPECTS OF USING ARTIFICIAL INTELLIGENCE FOR GENERATING ENERGY BAR RECIPES

The objects of research are energy bars developed using mathematical modeling and various artificial intelligence (AI) models, including ChatGPT, Gemini, and Claude. The paper analyzes the quality and shelf-life indicators of these products. The AI application in recipe addresses the challenge of overcoming the complexity of traditional mathematical modeling for the rapid optimization of multi-component recipes. This ensures the creation of energy bars with an enhanced nutritional profile without compromising their sensory and structural-mechanical properties.

The "Horikhovo-fruktovyi" sample consisted of oat flakes, dried cranberries, and prunes with a nut mix of almonds and peanuts, and chaenomeles. The composition of the "Shypshyna" bar was generated by the Claude AI model and contained whey protein and oat flakes, as well as rosehip, honey, and nuts. The "Askorbinka" sample, generated by Gemini, contained soy components: protein isolate, milk powder, and oat flakes. The recipe for the "Smorodyna" bar, generated by the ChatGPT model, included protein isolate, oat flour, and berry powders.

The use of AI allowed for an improvement in the protein profile. The protein content in the "Askorbinka" and "Smorodyna" recipes is 2.3 times higher than the protein content in the "Horikhovo-fruktovyi" sample. These data may be explained by the fact that AI databases contain information indicating that energy bars should have high protein content.

The organoleptic evaluation of the energy bars was carried out using a 25-point scale developed by the authors. Among the fresh products, the highest score (24) was achieved by the "Smorodyna" sample, the recipe for which was generated by ChatGPT.

The samples were stored for 14 days in various packaging materials. The sample generated by Claude exhibited the best organoleptic characteristics. Regarding moisture content and acid value, the "Horikhovo-fruktovyi" sample performed best, showing moisture values from 19.9% to 25% and an acid value ranging from 1.75% to 1.83% at the end of the storage period. It was established that parchment paper and foil possess the best barrier properties for sample storage.

***Keywords**: energy bars, shelf-life, organoleptic properties, consumer properties, artificial intelligence, food quality.*

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1. Introduction

Energy bars have become a popular source of energy and carbohydrates. Their sales in the UK market tripled between 2010 and 2015, reaching 137 million EUR, and their market in the US doubled over the same period to 2,314 million EUR [1]. The consumption of this product is increasing every year. This confirms the feasibility of expanding the energy bar market.

Protein-rich energy bars are known as a rational nutritional supplement for athletes, helping to build and repair connective tissues. The research [2] described the recipes of high-protein bars using lupin seeds, wheat germ and dried fruits, including raisins, dates, apricots and cranberries. The research confirmed that the content of phenols, flavonoids and fiber was significantly higher in the developed bars compared to the control sample. The author emphasizes the feasibility of using dried fruits and berry raw materials in bar recipes to improve nutritional value. However, it is important to maintain a rational ratio of components in the developed products.

The aim of the research [3] is to develop energy bars based on fruits enriched with fiber and protein with different ratios of fiber to protein in the control group (0:0), A (70:30), B (50:50) and C (30:70), as well as to evaluate their nutritional, physicochemical, antioxidant and organoleptic indicators. The results presented by the authors demonstrated that the developed samples had higher phosphorus content than the control group. Just as in the previous research, it was proven that in addition to the selection of recipe components, their ratio is decisive, which can be achieved by using mathematical modeling methods with the selection of specified parameters. Therefore, it is important to continue scientific research in the direction of expanding the methods of developing recipes.

In the research [4], energy bars based on dates were developed. Date paste was used as the main ingredient at a concentration of 55–90%. In addition, protein sources were used to obtain protein-enriched bars: skimmed milk powder, cereals or legumes. These ingredients significantly reduced the moisture content, reducing the brittleness of the bars to acceptable values. It should be noted that from an economic point of view, the use of dates as a base for bars is unjustified due to the high cost of dates on the market. Therefore, when selecting new recipes, it should be taken into account that in addition to nutritional and biological value, the cost of the product is also important for the consumer.

In the research [5], it was noted that the introduction of a food additive of iron in an amount of 1.0 and 3.0% to the recipe mixture increases the ash content by 1.35 and 1.37 times; the iron content by 1.27 and 1.29 times; the content of other minerals by 1.52 ± 0.75%; vitamins by 1.36 ± 0.41%; protein by 1.16 and 1.18 times; carbohydrates by 0.53 ± 0.02%; and fat by 3.40 ± 0.02. And the optimal mass fraction of the iron food additive is determined as 3.0%. This proves the thesis that the main difficulty in developing energy bar recipes lies not so much in the selection of raw materials, but in their rational ratio.

It should be noted that the analysis of the above scientific researches provided for the use of mathematical modeling for developing recipes. There are various methods and tools for mathematical modeling in food production. Thus, in the research [6], the Simplex Lattice Design method and the response surface methodology (RSM) were used to develop the energy bar recipe. The result was functional recipes for bars with cassava flour, bambara nut and cashews. The research [7] presents the use of linear programming methods in Microsoft Excel (using the Solver tool) to optimize the recipe for a high-protein energy bar. The solution to the problem was to maximize the protein content in a 50 g serving while adhering to the constraints of energy value (≤250 kcal), sugar content (≤12 g) and cost (≤0.80 euros). The basis for the preparation of the bars were: oats, whey protein, honey, peanut butter, dried fruits and a nut mixture. Mathematical modeling (e. g. linear programming) works when it is necessary to balance 3–5 ingredients, but when it is necessary to develop a multi-component product, the complexity of the calculations increases exponentially. Therefore, new tools should be sought that can better cope with multi-factor optimization.

The rapid transformation of technologies encourages to consider the possibilities of artificial intelligence for developing new products and modeling diets. Thus, in the work [8] it is stated that by 2050 the world population will increase by 10 billion, which will require fundamental changes in providing everyone with sustainable nutrition. In particular, the authors investigated the potential of artificial intelligence (AI) in the field of developing new food products, analyzing data necessary for creating new products.

In the publication [9] it is stated that artificial intelligence quickly changes recipes, improving existing ones and providing personalized recommendations based on individual tastes, can quickly generate and evaluate a large number of recipe options, which allows more effective experimentation and discovery of new flavor combinations. However, it should be noted that the components from which AI offers to develop recipes have already been sufficiently studied, so the main problem is the search for rational ratios that would satisfy both the organoleptic and nutritional parameters of products.

The paper [10] also describes the obstacles to the use of artificial intelligence in the food industry, in particular legal regulation (especially in the context of GDPR regulations); data confidentiality and security; personnel difficulties, because not all food industry workers can use AI correctly. Therefore, an important scientific issue is the correctness of human communication with artificial intelligence and the correct description of processes.

In the paper [11], the author compares different models of artificial intelligence for the classification and identification of food products using the example of white granulated sugar. It is logical that artificial intelligence could be used not only for the identification of food products and their research, but also for the creation of new products.

The source [12] describes in detail how artificial intelligence is used in the food value chain. In particular, the following key opportunities for using AI in the food chain are identified: quality control and food safety (for example, an AI-based computer vision system). Reducing waste through food demand and inventory forecasting can also be an AI result. AI speeds up the recipe development process by simulating ingredient mixes and predicting consumer acceptance. Mondelez's use of the AI platform reduced product development time by 4–5 times, leading to a 5.4% increase in sales and faster introduction of innovations such as the gluten-free Golden Oreo. It is found that when integrated with complementary methods such as the Internet of Things (IoT) and big data, AI can help drive new product development, food process modeling and optimization, and improved food quality and safety monitoring.

Practical applications of AI in recipe development are described in [13]. In particular, Kraft Heinz formed a joint venture with NotCo to develop plant-based products. The goal was to use the Giuseppe AI tool to develop high-quality products.

The problem of using artificial intelligence in creating recipes is to create a special autoencoder that accepts natural language queries and generates new recipes at the output. It should consist of two submodels: an encoder (converts input data into a numerical representation) and a decoder that converts numerical values into recipes.

The source [14] defines the main areas of artificial intelligence, including machine learning, computer vision, natural language processing, artificial neural networks, robotics, and expert systems. These subsets can be used in decision-making at different stages of the food chain.

The scientific questions that arise from the literature review are as follows: what functions of artificial intelligence should be implemented in the food product development process; whether it can replace traditional mathematical modeling when creating new recipes; and what should be the technical task for developing a rational recipe using AI.

Some of these issues are covered in scientific sources. For example, in the article [15] it is stated that artificial intelligence is part of the fourth industrial revolution in the food industry. The authors define the main advantages of AI in food production as the ability to analyze large data sets and make quick decisions at all stages of the food chain. Based on this research, it can be concluded that having data on the nutritional value and organoleptic characteristics of a large number of products, artificial intelligence can quickly perform multi-criteria optimization of recipes that will satisfy consumers in many parameters simultaneously.

However, it should be noted that the first step in applying AI in food production is to determine the purpose of its use. Thus, the source [16] states that there are two different types of AI – non-generative and generative. Non-generative AI analyzes data without creating new data, while generative AI creates new data that is similar to existing data. The article states that artificial intelligence is able to optimize and improve recipes in many parameters, including predicting the shelf life.

Despite the large number of individual studies related to the development of energy bars, the use of artificial intelligence to generate their recipes is still poorly studied. This makes the research relevant.

The objects of research are the "Horikhovo-fruktovyi" bar (developed by mathematical modeling) and bars generated by AI models: ChatGPT, Gemini, Claude.

The aim of research is to determine the prospects for using artificial intelligence to generate energy bar recipes. Based on the set goal, the research tasks are:

1) to develop energy bars using mathematical modeling methods and artificial intelligence models Chat GPT, Gemini, AI Claude;

2) to compare the organoleptic indicators of the developed energy bars;

3) to investigate the nutritional value of energy bars;

4) to investigate the preservation of the developed energy bars: to determine the change in organoleptic indicators, humidity and acidity during storage for 14 days depending on different packaging methods;

5) to carry out mathematical and statistical processing of the obtained data.

2. Materials and Methods

2.1. Modeling of energy bar recipes

To develop energy bar recipes, mathematical modeling of recipe compositions by the simplex method using linear algebra class problems was used. During mathematical modeling, it is important to note what will be the given parameter of the function [17].

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In order to expand the range of functional products, it was decided to analyze possible energy bar recipes formed using artificial intelligence tools. To generate new energy bar recipes, the artificial intelligence models ChatGPT (model GPT-4o), Gemini (model 1.5 Pro), Claude (model 3.5 Sonnet) were used. The artificial intelligence systems were tasked with developing energy bar recipes with improved nutritional value and high organoleptic properties of fortified and high-protein energy bar recipes.

2.2. Organoleptic evaluation of energy bars

To develop a scoring scale for evaluating the organoleptic indicators of energy bars, an expert method was used [18]. The following parameters were used: taste (P_1), aroma (P_2), consistency (P_3), appearance (P_4), given in Table 1.

Table 1

A 25-point scale for evaluating the organoleptic characteristics of energy bars was developed

Indicator	Weighting factor	Maximum sum of points taking into account weighting factors
Consistency (P_1)	1.0	5.0/5.0
Appearance (P_3)	1.0	5.0/5.0
Aroma (P_4)	1.5	5.0/7.5
Taste (P_5)	1.5	5.0/7.5
Total	–	25.0

The expert group used weighting factors for two organoleptic indicators: taste and aroma. These indicators are decisive for consumers. The maximum sum of points for all indicators is 25.

2.3. Methods of studying the physicochemical indicators of energy bars

The nutritional value of the products was determined by the calculation method [19].

The mass fraction of moisture was determined by drying to constant mass at a temperature of 105°C according to DSTU 4910:2008 "Confectionery. Methods for determining the mass fraction of moisture and dry matter" [20].

The acidity (mass fraction of titrated acids) was determined by the volumetric titration method [21].

2.4. Energy bars safety research

The following types of packaging were selected for the safety of energy bars:

1) transparent food-grade PE stretch film, 8 μm thick, made of linear low-density polyethylene (LLDPE), PE stretch film, Ukraine;

2) parchment paper for food products (cellulose), 50 g/m^2 thick, siliconized, "PacketPak", Ukraine;

3) aluminum foil for food products, 14 μm thick, Professional Line, Ukraine (Fig. 1).

Fig. 1. Samples of energy bar packaging

Storage was carried out at a temperature of 18°C and a relative humidity of 75%. The research of preservation indicators was carried out using an accelerated kinetic method.

2.5. Mathematical and statistical data processing

All researches were performed with 5-fold repeatability. The arithmetic mean and standard error of the mean were calculated. To study the relationship between the obtained data, the Pearson linear correlation coefficient was used. The obtained data were processed using the Microsoft Excel 2021 software package.

3. Results and Discussion

3.1. Development of energy bar recipes based on mathematical modeling and artificial intelligence algorithms

The first sample of the energy bar was developed using the mathematical modeling method, which is described in section 2.

The limit on the total ingredients in the recipe was determined by the formula

$$\sum_{i=1}^{j} x_i = 1000, \quad (1)$$

where x_i, i = 1, 2, ..., j – unknown amount of raw material of the i-th type (g).

Ensuring the required moisture content was determined by the formula

$$0.05\sum_{i=1}^{j} x_i \le \sum_{i=1}^{j} \lambda_i x_i \le 0.1\sum_{i=1}^{j} x_i, \quad (2)$$

where x_i, i = 1, 2, ..., j – unknown amount of raw material of the i-th type (g); λ_i – water content in 1 g of the i-th ingredient (g).

The specified parameter is to improve nutritional value by increasing protein content at moderate energy value. The solution of the problem was performed in the MatCad program. The main goal of creating the product was to provide the body with readily available sources of energy, as well as biologically valuable nutrients, in particular proteins, complex carbohydrates and polyunsaturated fatty acids. The sources of these components in the recipe were oatmeal, nuts and dried fruits. Additionally, crushed chaenomeles fruits were introduced into the product, which is a natural source of vitamin C and organic acids [22]. The use of this raw material allows to increase the antioxidant properties of the product and enrich it with biologically active compounds. The beneficial properties of chaenomeles were proven in the research [23].

The recipe in percentage ratio consists of the following components (Table 2).

Table 2

Recipe of the "Horikhovo-fruktovyi" energy bar

Raw materials	Fraction, %
Dried cranberries	10%
Dried prunes	15%
Almonds	15%
Peanuts	15%
Oatmeal	30%
Honey	10%
Chaenomeles	5%

The technology for making the bar involved preliminary preparation of the main components. Oat flakes were dried in an oven at a temperature of 120–140°C until a light nutty aroma appeared, after which they were ground to a coarse fraction. Dried fruits and nuts were ground to a homogeneous consistency and mixed with prepared oat flakes and crushed chaenomeles fruits.

The resulting mixture was combined with honey, which served as a natural sweetener and structure-forming agent. The finished mass was thoroughly mixed to a homogeneous consistency, after which bars were formed in appropriate molds. The formed products were placed in a freezer for 30–60 min to stabilize the structure. After cooling, the bars were removed from the molds and packed in food packaging material.

Other samples were developed by AI models ChatGPT (model GPT-4o), Gemini (model 1.5 Pro), Claude (model 3.5 Sonnet). As a result, several variants of recipes were obtained, which are given in Tables 3–5.

The Claude system is positioned as a standard of logical inference and cognitive accuracy, it is capable of generating large volumes of texts and analyzing data. The 'Shypshyna" recipe is presented in Table 3.

Table 3

Recipe of the "Shypshyna" energy bar (Claude)

Raw materials	Fraction, %
Dried rose hips	15%
Whey protein	20%
Oat flakes	20%
Almonds	15%
Honey	10%
Jerusalem artichoke syrup	10%
Dried cranberries	5%
Chia seeds	2%
Dried orange	3%

The formula presented in Table 3 is distinguished by the introduction of rose hips into the energy bar, which contributes to vitaminization and a significant amount of protein (20%).

The Gemini model is distinguished by its unique ability to process large amounts of information. With its use, the "Askorbinka" formula was generated (Table 4).

Table 4

Recipe of the "Askorbinka" energy bar (Gemini)

Raw materials	Fraction, %
Soy milk powder	10%
Soy protein isolate	35%
Oat flakes	30%
Invert syrup	10%
Jerusalem artichoke syrup	10%
Glycerin	4%
Ascorbic acid	1%
Dry lecithin	10%

The "Ascorbinka" energy bar, generated by Gemini, contained soy components such as protein isolate and milk powder, as well as oatmeal functionally enriched with ascorbic acid, lecithin and glycerin based on invert syrup.

ChatGPT's functionality is based on a high level of multimodal integration and adaptability to natural language. Using this model, the recipe for the "Smorodyna" bar was generated (Table 5).

Table 5

Recipe for the "Smorodyna" energy bar (Chat GPT)

Raw materials	Fraction, %
Rosehip powder	8%
Inulin	15%
Oat flour	25%
Protein isolate	35%
Freeze-dried currants	7%
Jerusalem artichoke syrup	10%

Given that artificial intelligence is able to generate new recipes based on the database it contains and quickly optimize multi-criteria problems, the recipe development process is facilitated, since there is no need to solve complex mathematical models. However, since the direction of recipe development using AI is relatively new, it is worth checking the rationality of the proposed recipes. Since the task was to develop energy bars with improved nutritional value, the Harrington desirability function was used. In particular, the desired product is a bar that, with high protein content, has a moderate energy value. The quality of the recipe is assessed as follows: 0.80–1.00 – very good, 0.63–0.80 – good, 0.37–0.63 – satisfactory, less than 0.37 – unsatisfactory. Mathematical calculations were carried out according to the methodology given in the source [24].

The generalized desirability is calculated as the geometric mean

$$D=\sqrt[3]{d_1 d_2 \ldots d_n}, \tag{3}$$

where d_1, d_n – the parameters to be optimized.

Analysis of the calculations of the values of the partial and generalized Harrington desirability functions for the three recipes that were developed by AI demonstrates mathematical optimization of the composition. The recipe developed by Claude showed a high level of functionality ($D = 0.81$). However, the recipe generated by Gemini has a value of $D = 0.90$ due to a significant increase in protein with the introduction of isolate and moisture-retaining components. The recipe developed by the ChatGPT model reached a maximum of $D = 0.94$, since the replacement of high-calorie fat components with inulin allowed to increase the protein content $d_1 = 0.96$ and optimize the energy value $d_2 = 0.92$, which makes it the most rational within the given criteria. Despite the mathematical processing of the data obtained from the recipes, additional experimental studies of consumer properties were conducted, which are presented in the next section. At the same time, it should be noted that writing prompts for artificial intelligence using mathematical processing of the obtained data speeds up and facilitates the development of recipes compared to mathematical modeling methods.

The technology for preparing energy bars proposed by artificial intelligence systems was similar to the basic technological scheme. At the first stage, dry ingredients (cereal components, protein isolates, nuts and powdered additives) were ground and thoroughly mixed until a homogeneous mixture was obtained.

Then, liquid components were introduced into the mixture – honey or syrups (in particular, Jerusalem artichoke syrup or invert syrup), which performed the function of a sweetener and binding agent [25]. After thorough mixing, the resulting mass was formed into bars using molds. To stabilize the structure, the formed products were also placed in a freezer for a certain time.

A photographic image of the samples is shown in Fig. 2.

Thus, 4 energy bar recipes were proposed for further research into organoleptic characteristics, nutritional value and shelf life.

Fig. 2. Produced samples of energy bars

3.2. Organoleptic evaluation of developed energy bars

Photos of developed samples prepared for tasting by 4 experts are shown in Fig. 3.

The results of the organoleptic evaluation of the samples according to the parameters "appearance", "consistency", "taste" and "aroma" are shown in Fig. 4.

Taste is decisive for the consumer when choosing a product. The leader in this indicator is sample No. 4 "Smorodyna" with a score of 7.5. Sample No. 3 "Ascorbinka" scored the lowest number of points, 6.375, although even this indicator can be considered quite high. The best aroma indicators (7.5) are samples No. 2 "Shypshyna" and No. 4 "Smorodyna", however, the sample ("Horikhovo-fruktovyi"), which was developed using the method of mathematical modeling, was significantly inferior in aroma (6.75). At the same time, according to the parameter "consistency", the sample "Horikhovo-fruktovyi" received the highest score (5). Along with it, sample No. 3 "Ascorbinka" was highly rated. According to the parameter "appearance", most samples (No. 1, No. 2, No. 4) received the same score – 4.75. These data indicate that artificial intelligence can compete with the traditional method of mathematical modeling in order to develop new recipes that are distinguished by high taste properties. A comprehensive assessment of organoleptic parameters is shown in Fig. 5.

a *b* *c* *d*

Fig. 3. Appearance of the developed samples: *a* - "Smorodyna"; *b* - "Ascorbinka"; *c* - "Shypshyna"; *d* - "Horikhovo-fruktovyi"

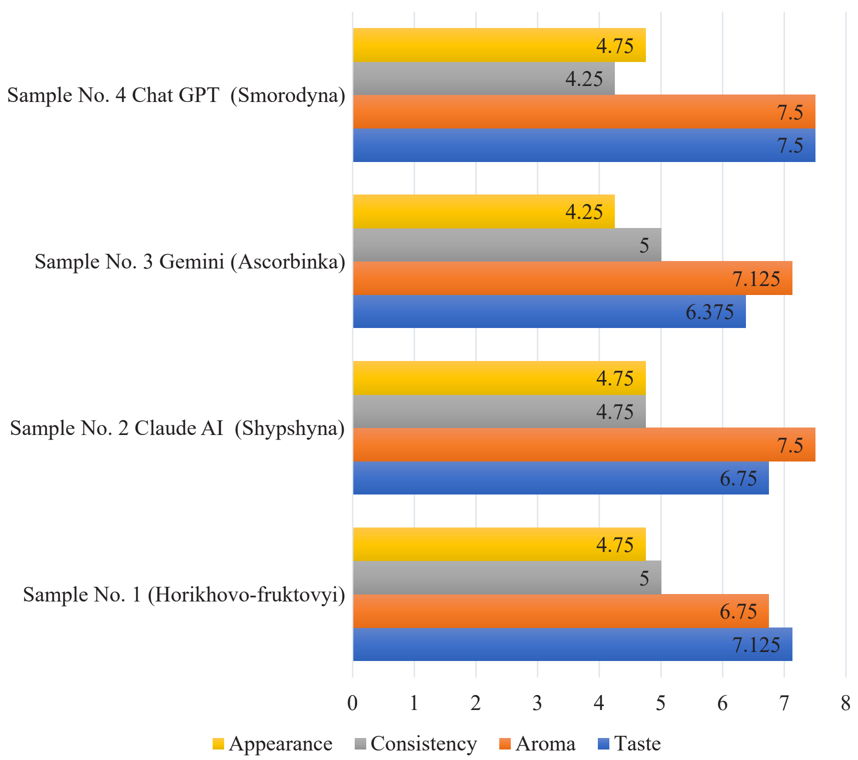

Fig. 4. Organoleptic evaluation of the developed energy bars

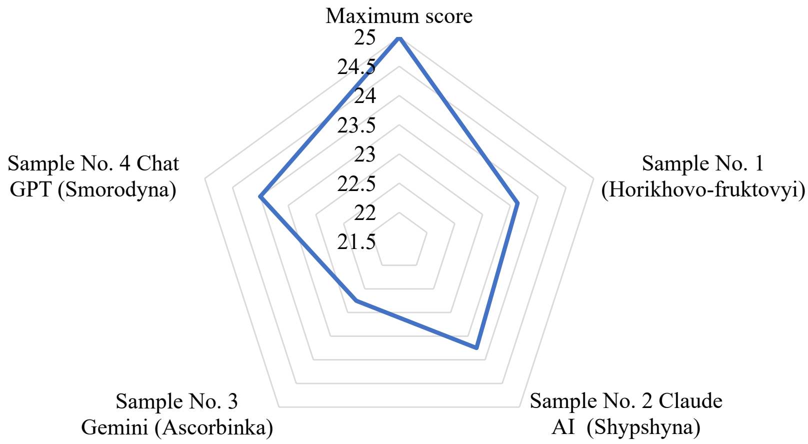

Fig. 5. Results of a comprehensive evaluation of energy bar samples by organoleptic indicators

to fats. In recipe No. 2, the protein content increased by 54%, and the maximum protein content (36.8 g/100 g) was recorded in the "Ascorbinka" recipe.

But it is recipe No. 4 "Smorodyna" that is the most balanced for the modern market, as it was possible to obtain the maximum response in terms of protein content (d = 0.96 on the Harrington desirability scale) and at the same time minimize the energy value to 312.8 kcal. The lowest energy value characteristic of recipe 4 is explained by the reduced fat content and the use of functional ingredients, in particular inulin. Such a task is quite complex for mathematical modeling, so artificial intelligence has shown its effectiveness in achieving the set goal.

Thus, all developed samples demonstrated high organoleptic properties. The "Smorodyna" sample, the recipe of which was generated by ChatGPT, scored 24 out of 25 possible points by sensory characteristics, which indicates the prospects of using artificial intelligence in creating products with original taste and aroma.

3.3. Research on the nutritional value of energy bars

In order to assess the nutritional value of the proposed recipes, their nutritional and energy value were calculated. The results obtained are given in Table 6.

Analysis of the data obtained showed that the recipes differ significantly in nutritional value. Analysis of the nutritional value of the recipe of the "Horikhovo-fruktovyi" energy bar indicates that the product only minimally meets the requirements for high-protein products, and the energy value is formed due

3.4. Research on the safety of energy bars

In energy bars, the mass fraction of moisture is normalized; its decrease can lead to loss of taste properties and deterioration of consistency and appearance. The research results of the loss of moisture content for 14 days by the accelerated kinetic method depending on the type of packaging are shown in Fig. 6.

As can be seen from Fig. 6, all samples lost some moisture during storage, regardless of what they were packed in. Foil turned out to be the most effective barrier moisture-retaining material. Losses of the mass fraction of moisture of samples packed in foil are minimal for all bars and range from -0.1% "Horikhovo-fruktovyi" to -0.9% "Smorodyna". Parchment paper retains moisture the worst, which is logically explained by its porous structure, so it should not be used for packaging bars. The most stable sample in the context of moisture loss was the "Askorbinka" sample, which is explained by its recipe composition.

Table 6

Calculated nutritional value of energy bars, per 100 g

Indicator	Recipe 1 "Horikhovo-fruktovyi"	Recipe 2 "Shypshyna"	Recipe 3 "Ascorbinka"	Recipe 4 "Smorodyna"
Proteins, g	15.6	24.0	36.8	35.5
Fats, g	30.3	13.4	6.8	2.3
Carbohydrates, g	40.2	47.7	42.3	46.6
Energy value, kcal	462.1	392.9	372.4	312.8

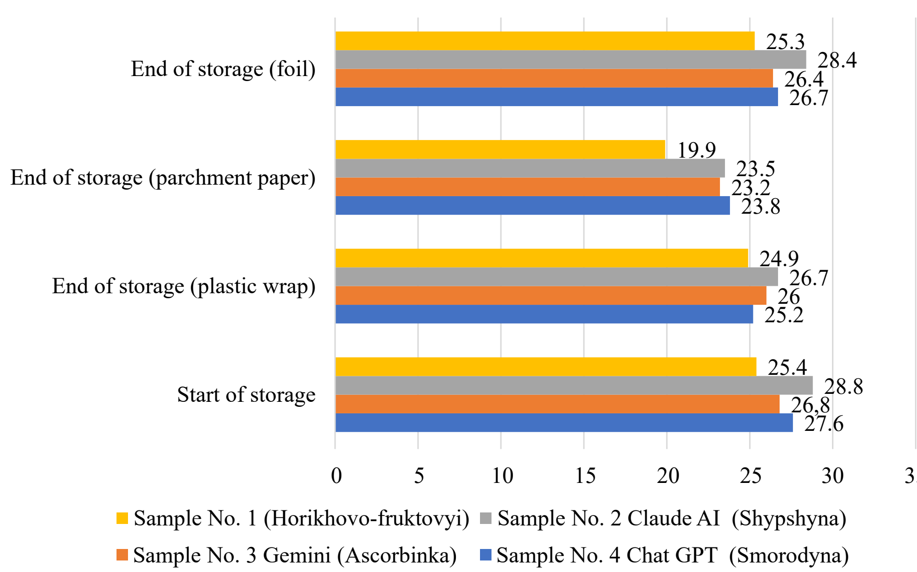

Fig. 6. Dynamics of changes in the mass fraction of moisture of energy bars during storage

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Since energy bars are characterized by a high proportion of fats, it is important to study the change in the lipid fraction during their storage (Fig. 7).

For all samples without exception, the acid number increased on the 14th day of storage, regardless of what they were packed in. Food film turned out to be the least effective for the "Shypshyna" (the indicator increased to a maximum of 2.58%) and "Smorodyna" (2.51%) samples. Foil is the most effective packaging material for all energy bars. It should be noted that it also confirmed its high properties for preserving moisture in the samples.

Despite the accumulation of acid number in all samples, it should be noted that within 14 days their value did not reach a critical maximum. However, since synthetic food additives, in particular antioxidants were not added to the recipe of the developed energy bars, their shelf life may be somewhat lower than that of industrially produced energy bars.

The evaluation of the organoleptic indicators of the products after 14 days of storage is shown in Fig. 8–10.

Fig. 8, in particular, shows the data on the organoleptic indicators that were stored in the film.

From the data of Fig. 7 it is clear that the highest indicators of taste and aroma are distinguished by the "Smorodyna" sample (7.5 points, respectively). It did not lose its sensory characteristics at all during storage.

At the same time, the sample developed by the method of mathematical modeling had the worst indicators of taste and aroma at the end of storage in food film.

The results of organoleptic examination of samples stored in parchment paper are shown in Fig. 9.

The "Askorbinka" sample had the worst taste indicators after 14 days of storage in parchment paper, on a par with other samples. The "Shypshyna" sample had the best taste and aroma. The "Smorodyna" sample had a fairly high aroma indicator, although in terms of appearance this sample significantly lost to the others (3.75 points). Fig. 10 shows the evaluation of samples after 14 days of storage in foil.

The figure shows that after 14 days in foil, the "Shypshyna" sample did not change its taste and aroma at all (7.5 points, respectively), the "Smorodyna" sample did not change its aroma, and the "Horikhovo-fruktovyi" sample had the worst taste qualities.

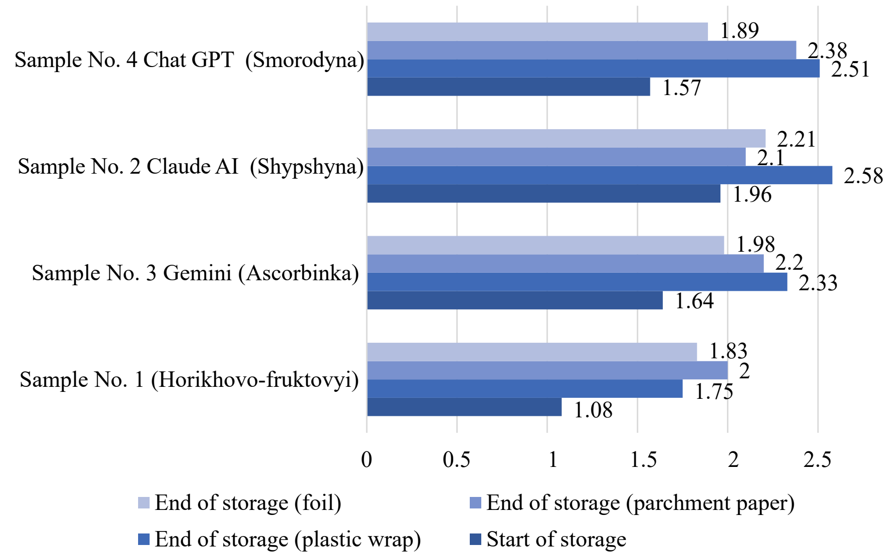

Fig. 7. Dynamics of changes in acid number during 14 days of storage

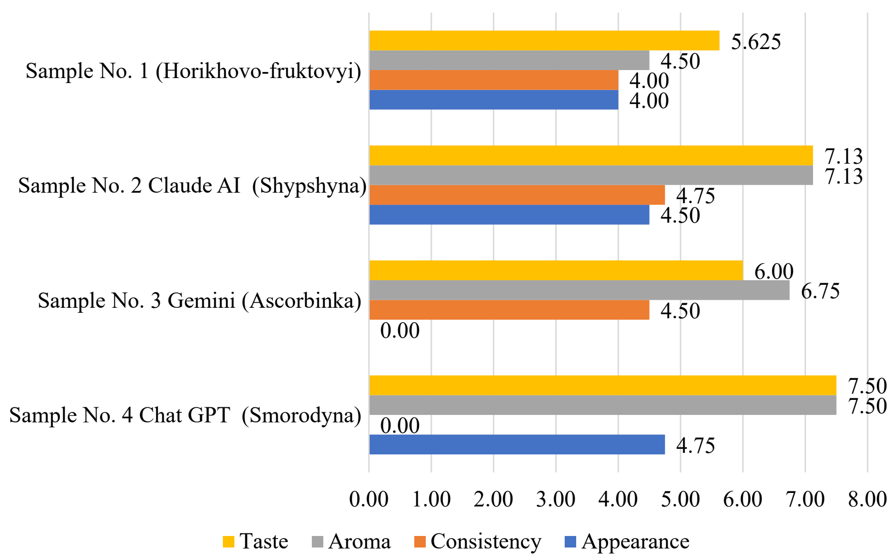

Fig. 8. Organoleptic evaluation of samples after 14 days of storage in film

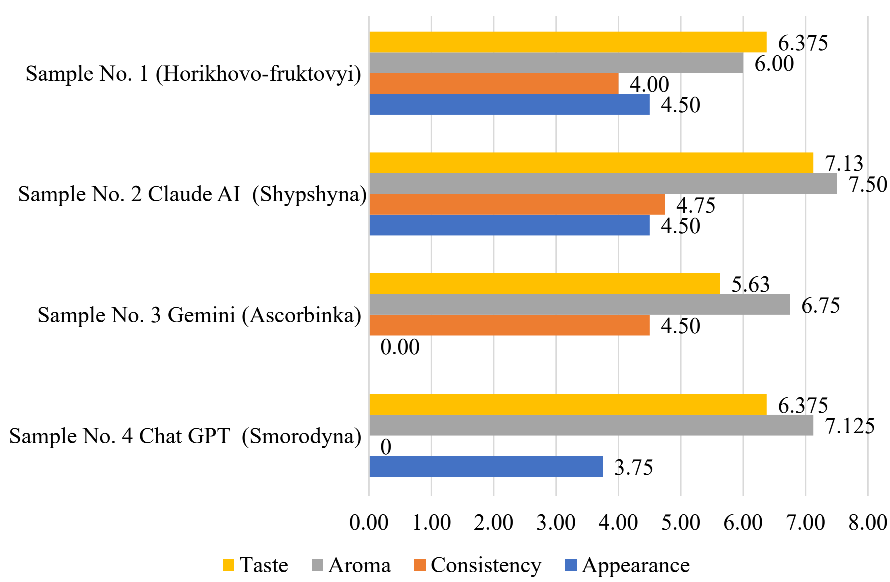

Fig. 9. Organoleptic evaluation of samples after 14 days of storage in parchment paper

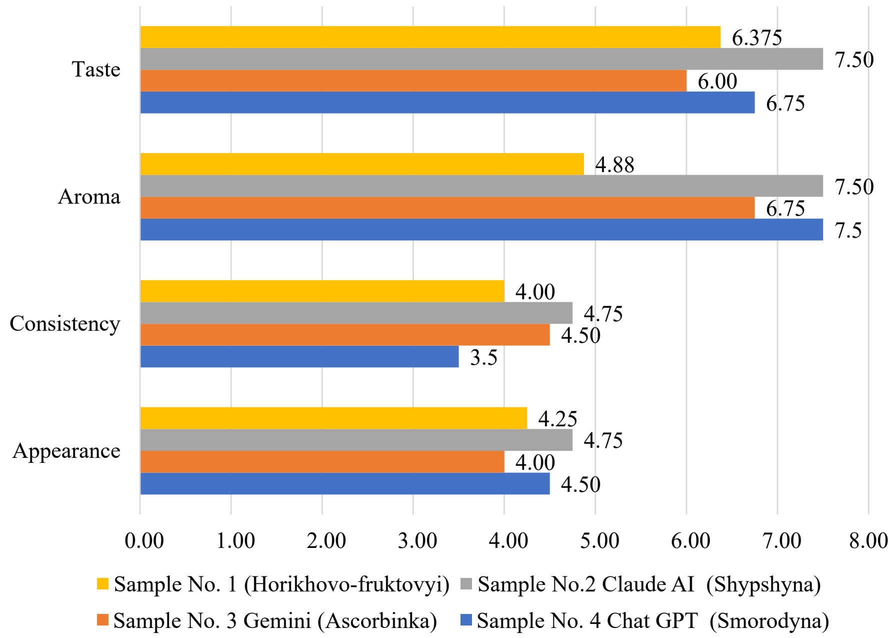

Fig. 10. Organoleptic evaluation of samples after 14 days of storage in foil

For long-term storage (more than 14 days) of the studied energy bars, foil should be preferred, since it creates a hermetic barrier that protects the product from foreign odors and moisture better than polymer film or paper. The research data give reason to believe that there is no unambiguous answer to the question of whether artificial intelligence can develop a recipe with better indicators for preservation. Obviously, all specified parameters of the recipe and the initial product should be described as clearly as possible in the process.

3.5. Mathematical and statistical processing of results

The Pearson linear correlation coefficient allows to assess the closeness and direction of the relationship between two characteristics studied in one sample. The coefficient reflects the level of proportional dependence between variables and is effective only for identifying linear patterns. That is why a research of the correlation between the change in acid number and mass fraction of moisture after 14 days of storage in different samples and different types of packaging was carried out. The results are given in Table 7.

Table 6

Correlation analysis of the relationship between the indicators of the safety of the studied energy bars

Research object	Correlation coefficient (r_{emp})	Significance level ($p \leq 0.05$)	Significance level ($p \leq 0.01$)	Conclusion about the relationship
"Smorodyna"	–0.883	0.707	0.834	Strong, significant
"Ascorbinka"	–0.602	0.707	0.834	Moderate, insignificant
"Shypshyna"	–0.550	0.707	0.834	Moderate, insignificant
"Horikhovo-fruktovyi"	–0.945	0.707	0.834	Very strong, significant

The "Horikhovo-fruktovyi" and "Smorodyna" energy bars have the closest relationship between moisture dynamics and free fatty acid accumulation, regardless of the type of packaging. This means that for these products, lipid stability largely depends on moisture retention, and therefore packaging materials should provide protection against oxidation and not contribute to moisture loss. For the "Ascorbinka" and "Shypshyna" samples, the relationship is not statistically significant. This may mean that other factors, in particular the recipe composition, affect the spoilage of fats in these samples. The sample that was developed using mathematical modeling without the AI use is the most labile to the selection of packaging materials. This suggests that when generating recipes, artificial intelligence immediately takes into account aspects of product safety. However, this statement requires additional research.

3.6. Discussion of the research results

According to the results of the conducted research, it was found that the use of different artificial intelligence models for generating energy bar recipes does not provide a single optimal model that would surpass the others in all indicators.

The results obtained indicate the absence of a single pattern for the formation of consumer properties of recipes. This is due to the different approaches of the models to optimizing a given objective function. The scientific novelty of the obtained data lies in the fact that the comparative effectiveness of different AI models (GPT-4o, Gemini 1.5 Pro, Claude 3.5 Sonnet) in solving multi-criteria problems of optimizing food recipes has been established and the feasibility of combining recipe generation with classical methods of quality assessment (Harrington's desirability function) has been proven.

At the same time, each of the studied models demonstrated advantages according to individual product quality criteria. In terms of protein enrichment, the Gemini and ChatGPT models demonstrated the best results. In terms of organoleptic properties (taste, aroma, consistency, appearance), the best model was ChatGPT. In terms of organoleptic characteristics preservation during storage, Claude. This confirms the results of the research [25], which states that AI technologies can improve quality and nutritional value, while simultaneously increasing safety, traceability and efficiency of natural resource use in the food sector. In addition, the article [26] states that AI is able to improve the quality of food products using advanced modeling methods. The results obtained in the article confirm this thesis, but it is necessary to accumulate massive data that could be statistically substantiated.

The results obtained allow to conclude that different AI models actually implement different optimization strategies (even with the same process). In addition, no model provides multi-criteria optimality. Artificial intelligence can be used to generate options, but it does not always show effectiveness in making a final decision.

During the research, all artificial intelligence models received the same formalized request (promt), which contained a description of the objective function and recipe constraints. In particular, the need to maximize protein content while minimizing the cost and energy value of the product was specified. At the same time, the results obtained demonstrated that even under the same input conditions, different AI models generate different recipe solutions. This indicates that the interpretation of the prompt is ambiguous and depends on the internal algorithms of the models, the database and approaches to generating ready-made solutions. AI cannot be used to effectively solve mathematical models, but is a fairly good tool for interpreting a text description of the problem and generating a "probably relevant solution". This confirms the data of the authors [27], where the authors propose to apply the capabilities of artificial intelligence for the digitalization and automation of food supply chains and for the implementation of intelligent food production management systems. That is, artificial intelligence in food production is more useful for systematization and management than for the development of individual food products, where organoleptic properties are decisive.

The practical significance of research lies in studying the prospects of artificial intelligence for generating recipes and the possibility of using the developed energy bars for a balanced diet.

Martial law conditions in Ukraine have affected the conduct of experimental research, as access to laboratories and chemical reagents for conducting research has significantly decreased. The process of experimental work is complicated by air raids, which have to interrupt the course of research.

Prospects for further publications include studying the prospects of artificial intelligence in generating recipes for various food products with given parameters.

4. Conclusions

1. To generate new energy bar recipes, the artificial intelligence models ChatGPT, Gemini, Claude were used. The recipe for the "Horikhovo-fruktovyi" bar was created using mathematical modeling without the use of artificial intelligence. The recipe developed by Claude showed a high level of functionality ($D = 0.81$). The recipe generated by Gemini has a $D = 0.90$ value due to a significant increase in protein with the introduction of isolate and moisture-retaining components. The recipe developed by the ChatGPT model reached the maximum $D = 0.94$, since the replacement of high-calorie fat components with inulin allowed to increase the protein content.

2. The organoleptic evaluation of energy bars was carried out using the developed 25-point scale. According to the complex organoleptic assessment, the highest number of points (24) among fresh products was scored by the "Smorodyna" sample, the recipe of which was generated by ChatGPT. This sample demonstrated the best performance in terms of "taste" and "aroma" (7.5 points, respectively), which indicates a high harmony of the recipe composition.

3. The nutritional value of energy bars was determined by the calculation method. The use of AI tools allowed to significantly increase the protein content of the products. The "Ascorbinka" recipe and the "Smorodyna" recipe are leaders in protein content (36.8 g and 35.5 g, respectively), which is more than 2.3 times higher than the protein content in the energy bar developed by the method of mathematical modeling.

4. It was established that among the studied samples, the sample generated by Claude, which retained a high score regardless of the type of packaging, was the most stable organoleptic indicator during storage. The best packaging material for preserving organoleptic properties is parchment paper and foil, while stretch film demonstrated rather low barrier properties. When using foil, the dynamics of moisture change for all samples was minimal, from 0.1% to 0.7%. The most stable in terms of moisture content was the "Horikhovo-fruktovyi" sample, which lost 0.5% in the film and 0.1% in the foil during 14 days of storage. This indicates a high water-holding capacity of its ingredients (nuts and dried fruits).

5. The correlation analysis confirmed a statistically significant strong and very strong relationship ($r \geq 0.883$ at $p \leq 0.01$) between the change in the mass fraction of moisture and the acid number for the "Smorodyna" and "Horikhovo-fruktovyi" samples. This indicates the dependence of the stability of lipids in these bars on the tightness of the packaging for these recipes. At the same time, for the "Askorbinka" and "Shipshyna" samples the connection was moderate, which indicates the determining influence of the recipe, not the packaging materials, on the preservation.

Conflict of interest

The authors declare that they have no conflict of interest in this research, including financial, personal, authorial or other, which could affect the work and its results presented in this paper.

Financing

The research was conducted without financial support.

Data availability

Data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they used artificial intelligence technologies to obtain experimental data, but did not use it in their interpretation. To obtain experimental data, the Gemini, ChatGPT, AI Claude models were used. The recipes obtained using AI generation are described in the second section of the article.

Authors' contributions

Alina Tkachenko: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review and editing; ***Olexandra Horobets***: Software, Validation, Formal analysis, Investigation, Resources, Data curation; ***Olena Goryachova***: Validation, Formal analysis, Investigation, Resources, Data curation; ***Olena Olkhovska***: Software, Validation, Formal analysis, Investigation, Resources, Data curation.

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