

[https://doi.org/10.52326/jes.utm.2024.31\(3\).07](https://doi.org/10.52326/jes.utm.2024.31(3).07)

UDC 004.42:613.2



## INTEGRATION OF A DATA-DRIVEN SOFTWARE APPLICATION AND A MULTIMODAL LARGE LANGUAGE MODEL FOR ENHANCED NUTRITIONAL GUIDANCE: A CASE STUDY

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Received: 07, 18, 2024

Accepted: 08, 19, 2024

**Abstract.** In the realm of health and wellness, the integration of data-driven technology and artificial intelligence (AI) has opened up new possibilities for personalized and data-driven approaches. HN-Assistant, a software application designed to analyze an individual's nutritional state and provide tailored recommendations, offers a powerful tool for promoting healthy eating habits. The HN-Assistant can also analyze how good a food product is at covering the estimated nutrient requirements. However, when combined with the capabilities of advanced AI assistants based on LLMs, the potential for comprehensive and insightful nutritional guidance is taken to new heights. This paper describes an attempt at integrating the proprietary software application HN-Assistant with GPT-4o to empower final users to make better nutritional decisions. The application was built in R programming language using the Shiny package, and the interaction between HN-Assistant and GPT-4o is based on an API in Python.

**Keywords:** *software application; data-driven analytics; nutrition; artificial intelligence; large language model.*

**Rezumat.** În domeniul sănătății și al bunăstării, integrarea tehnologiei bazate pe date și a inteligenței artificiale (AI) a deschis noi posibilități pentru abordări personalizate și bazate pe date. HN-Assistant, o aplicație software concepută pentru a analiza starea nutrițională a unui individ și pentru a oferi recomandări personalizate, reprezintă un instrument puternic pentru promovarea obiceiurilor alimentare sănătoase. HN-Assistant poate analiza, de asemenea, cât de bun este un produs alimentar pentru a acoperi cerințele estimate de nutrienți. Cu toate acestea, atunci când sunt combinate cu capacitățile asistenților AI avansați bazați pe LLM, potențialul de îndrumare nutrițională cuprinzătoare și perspicace este dus la noi culmi. Această lucrare descrie o încercare de integrare a aplicației software proprietare HN-Assistant cu GPT-4o pentru a permite utilizatorilor finali să ia decizii nutriționale mai

bune. Aplicația a fost construită în limbajul de programare R folosind pachetul Shiny, iar interacțiunea dintre HN-Assistant și GPT-4o se bazează pe un API în Python.

**Cuvinte cheie:** *aplicație software; analiză bazată pe date; nutriție; inteligență artificială; model de limbaj mare.*

## 1. Introduction

In today's fast-paced world, it can be challenging to make informed decisions. Fortunately, technological advancements have led to the development of software applications that aid users in making more knowledgeable decisions, especially when combined with the capabilities of large language models (LLMs). One of the areas which can benefit from such a combination is healthy nutrition.

With many food choices available today, determining which options genuinely benefit our health can be challenging. International organizations like the European Food Safety Authority (EFSA) [1], the Food and Drug Administration (FDA) [2], the World Health Organization (WHO) [3], and others play a vital role in providing recommendations for healthy nutrition. These organizations use their expertise and global reach to develop evidence-based guidelines that inform policies, regulations, and public health initiatives. By promoting safe and nutritious food choices, these recommendations contribute to the well-being of populations worldwide and help address global health challenges. Individuals, policymakers, and food industry stakeholders must rely on and implement these recommendations to foster healthier eating habits and improve public health on a global scale.

The web-based software application Healthy Nutrition Assistant (HN-Assistant) [4,5] was the first step towards helping users make more informed decisions about their nutrition. It excels in calculating essential parameters such as Body Mass Index (BMI) [6,7], Basal Metabolic Rate (BMR) [8-10], and Total Daily Energy Expenditure (TDEE) [11,12]. It also provides detailed recommendations for daily macronutrients, vitamins, and mineral requirements based on an individual's unique profile.

By generating visual representations of the nutrient distribution through radar charts, the HN-Assistant offers a clear and concise overview of the nutritional adequacy of a given food product or dietary plan.

The application was built using concepts primarily based on EFSA recommendations.

The integration of data-driven software applications like HN-Assistant with multimodal language models such as GPT-4o represents the next step in the advancement of personalized nutrition. HN-Assistant provides detailed nutritional evaluations based on user data, while GPT-4o can interpret and expand on these evaluations through natural language processing and multimodal capabilities.

This paper presents the mentioned software application and elaborates on its integration with an LLM, GPT-4o. The obtained synergy seems to offer a more comprehensive approach to nutritional guidance.

## 2. Materials and Methods

The HN-Assistant data-driven software application was built using the Shiny(R) package [13]. This package provides various tools and functionalities for creating an interactive and visually appealing nutrition application. With Shiny, developers can easily incorporate data visualization techniques, such as charts, graphs, and interactive dashboards,

to present nutritional information more engagingly and understandably. These visualizations can help users comprehend complex nutritional data and make more informed food choices.

Furthermore, Shiny applications can be easily deployed across various platforms, including desktops, smartphones, and tablets, making them accessible to a broader audience. This flexibility ensures that users can access the application whenever and wherever they need it, whether grocery shopping, dining out, or cooking at home. The application's convenience and portability further encourage users to engage with it regularly and consistently make healthier choices.

The LLM model used in this research is a generative pre-trained transformer (i.e., GPT-4o) [14], and the interaction between HN-Assistant and GPT-4o is based on an application programming interface (API) in Python [15].

### **3. Integrating the software application with an LLM**

#### **3.1. Multimodal language models: a versatile tool**

Multimodal language models like GPT-4o can process and generate text, images, and other data types, making them versatile tools for interpretation and communication. These models can analyze complex datasets, translate technical information into user-friendly language, and provide context-aware recommendations. Their ability to engage in interactive dialogue enhances user experience by offering personalized and adaptive advice.

#### **3.2. Synergistic integration**

Integrating HN-Assistant with GPT-4o allows for a more dynamic and interactive nutritional counseling experience. The data-driven insights from HN-Assistant can be seamlessly translated into actionable advice through GPT-4o's language capabilities. For instance, when HN-Assistant outputs nutritional deficiencies, GPT-4o can suggest specific foods or dietary adjustments to address these gaps, tailoring the advice to individual preferences and cultural contexts.

The integration provides a holistic user experience by combining precise data analysis with intuitive communication. Users receive not only raw data but also comprehensible guidance that considers their lifestyle and goals. This interactive approach can increase user engagement and adherence to nutritional recommendations.

The integrated system can adapt recommendations in real time through continuous learning and feedback mechanisms. As users input new data or preferences, the system can refine its advice, ensuring that nutritional guidance remains relevant and practical. This adaptability is crucial in addressing the dynamic nature of individual dietary needs.

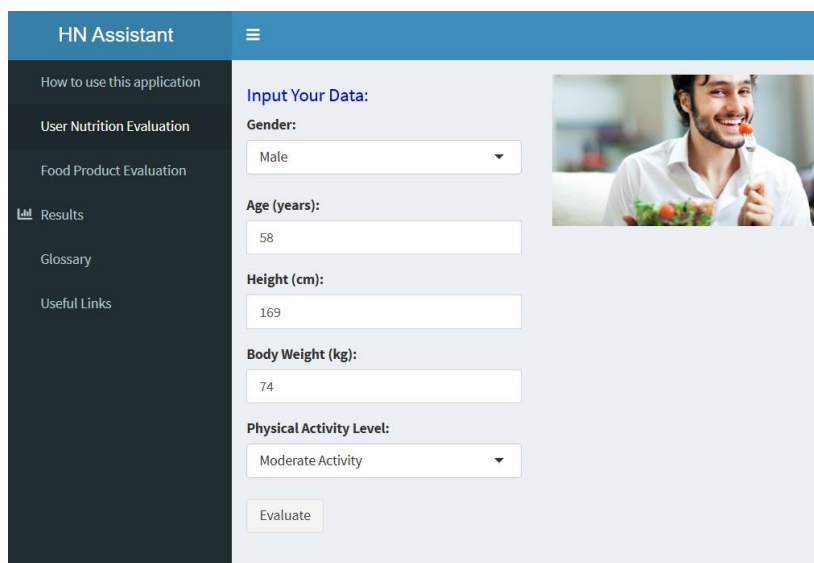
#### **3.3. Challenges and considerations**

Despite the potential benefits, integrating HN-Assistant with a multimodal LLM poses challenges. Ensuring data privacy and security is paramount, as sensitive health information is involved. Additionally, the system must be designed to avoid biases and inaccuracies that could arise from algorithmic processing. Continuous updates and validation against current nutritional science are necessary to maintain the credibility and reliability of the guidance provided.

## 4. Results

### 4.1. The use of the HN-Assistant application alone

The created software application prompts the user to input general information such as age, gender, weight, height, and level of physical activity (Figure 1).



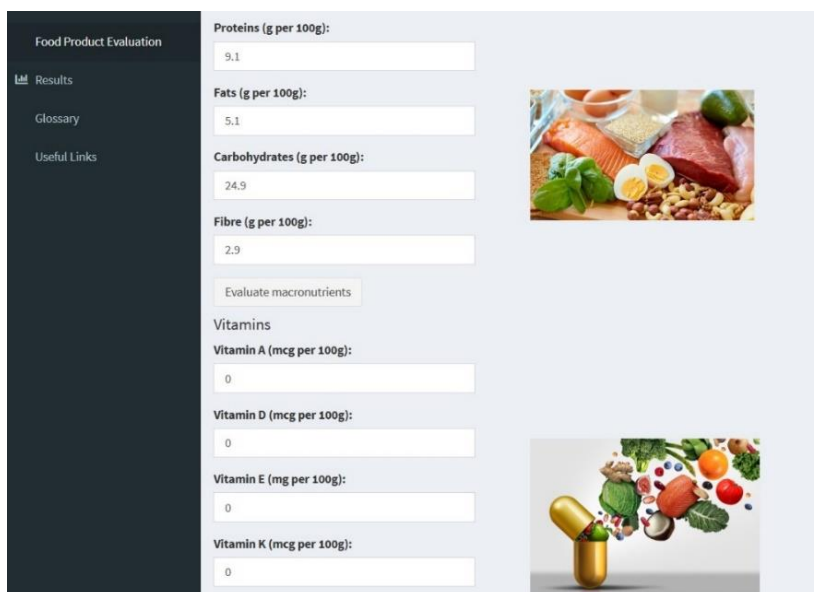
The screenshot shows the 'HN Assistant' application interface. On the left is a dark sidebar with navigation options: 'How to use this application', 'User Nutrition Evaluation', 'Food Product Evaluation', 'Results' (highlighted with a magnifying glass icon), 'Glossary', and 'Useful Links'. The main content area is titled 'Input Your Data:' and contains the following fields:
 

- Gender:** A dropdown menu with 'Male' selected.
- Age (years):** A text input field containing '58'.
- Height (cm):** A text input field containing '169'.
- Body Weight (kg):** A text input field containing '74'.
- Physical Activity Level:** A dropdown menu with 'Moderate Activity' selected.
- An 'Evaluate' button at the bottom.

 To the right of the form is a small image of a smiling man eating a carrot.

**Figure 1.** The interface for the input of the user data.

The application is also able to evaluate a food product of interest by inputting data available on the food product label (Figure 2).



The screenshot shows the 'Food Product Evaluation' section of the application. The sidebar is the same as in Figure 1. The main content area has the following fields:
 

- Proteins (g per 100g):** A text input field containing '9.1'.
- Fats (g per 100g):** A text input field containing '5.1'.
- Carbohydrates (g per 100g):** A text input field containing '24.9'.
- Fibre (g per 100g):** A text input field containing '2.9'.
- An 'Evaluate macronutrients' button.
- Vitamins:**
  - Vitamin A (mcg per 100g):** A text input field containing '0'.
  - Vitamin D (mcg per 100g):** A text input field containing '0'.
  - Vitamin E (mg per 100g):** A text input field containing '0'.
  - Vitamin K (mcg per 100g):** A text input field containing '0'.

 To the right of the form are two images: the top one shows a plate of salmon, eggs, and vegetables; the bottom one shows a golden capsule surrounded by various fruits and vegetables.

**Figure 2.** The interface for the input of nutrient content of a food product.

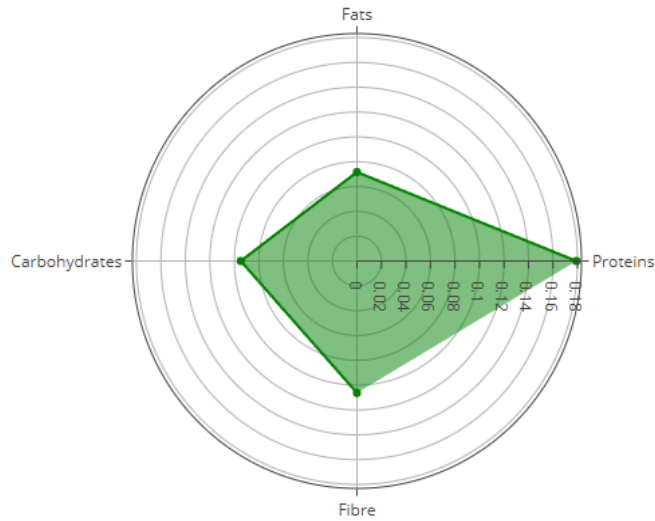
Based on this information, the application estimates several basic parameters concerning the user's nutritional state (e.g., BMI, BMR, and TDEE). It classifies the nutritional status of the user (e.g., normal or over/underweight, obesity, or malnutrition). Based on input information, it will also calculate daily nutrient requirements (e.g., macronutrients, vitamins, and minerals). The results of the analysis and estimations can be visualized by pressing the 'Results' icon on the left vertical panel of the application (Figures 1 and 2).

Table 1 presents the results provided by HN-Assistant for a 58-year-old male, 1.69 cm tall, weighing 74 kg, and showing moderate physical activity.

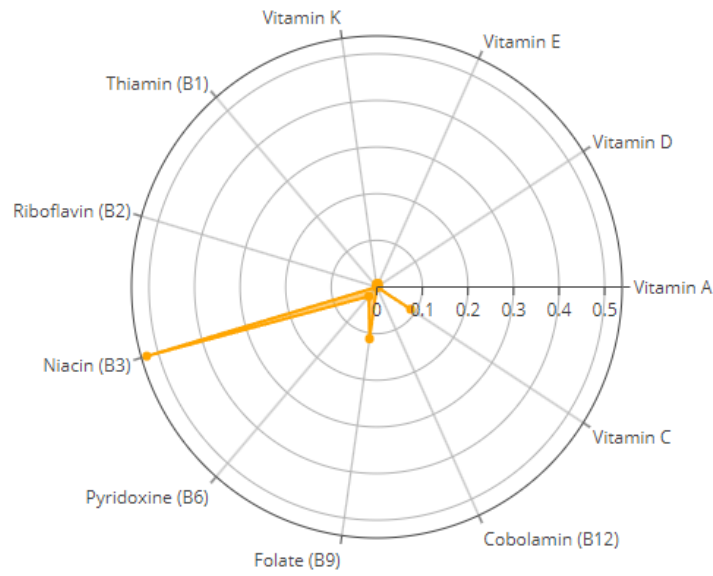
Table 1

<b>Estimation results for a 58-year-old individual</b>	
<b>Main Nutritional State Parameters</b>	
Your Body Mass Index is 25.9. Nutritional State - Overweight.	
Your Basal Metabolic Rate equals 1648 kcal.	
Based on Your Physical Activity Your Total Daily Energy Expenditure represents 2637 kcal.	
<b>Nutrient Requirements</b>	
<i>Your Daily Macronutrient Requirements</i>	
<b>Nutrient</b>	<b>Requirement</b>
Proteins (g)	61.40
Fats (g)	87.90
Polyunsaturated Fats (g)	29.30
Carbohydrates(g)	263.70
Added Sugars (max. g)	10.00
Fibre (g)	32.00
<i>Your Daily Vitamin Requirements</i>	
<b>Vitamin</b>	<b>Requirement</b>
Vitamin A (µg)	700.00
Vitamin D (µg)	15.00
Vitamin E (mg)	12.00
Vitamin K (µg)	70.00
Thiamin (B <sub>1</sub> ) (mg)	1.10
Riboflavin (B <sub>2</sub> ) (mg)	17.67
Niacin (B <sub>3</sub> ) (mg)	17.67
Pyridoxine (B <sub>6</sub> ) (mg)	18.77
Folate (B <sub>9</sub> ) (µg)	330.00
Cobolamin (B <sub>12</sub> ) (µg)	3.40
Vitamin C (mg)	110.00
<i>Your Daily Mineral Requirements</i>	
<b>Mineral</b>	<b>Requirement</b>
Potassium (mg)	3500.00
Calcium (mg)	950.00
Iron (mg)	11.00
Zinc (mg)	16.00

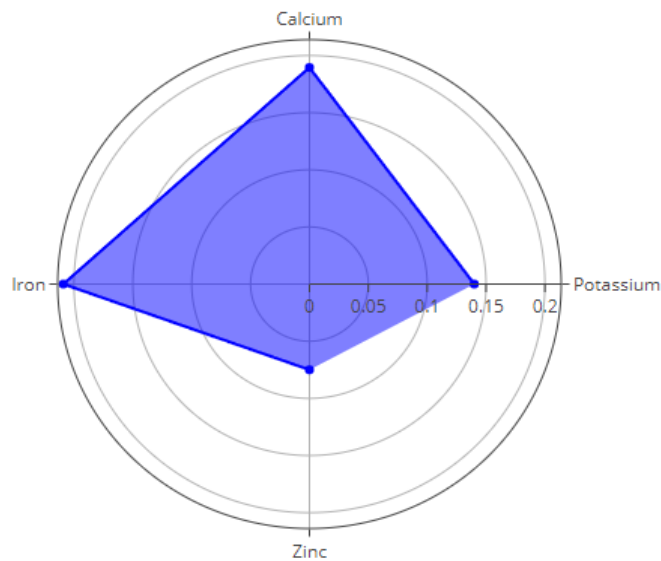
Then, the input of information concerning a food product of interest is followed. This information is available on the product label and is quantified for 100 g/mL. The application will estimate the coverage rate of certain nutrients by 100 g of product, comparing it with the requirements values calculated in the previous step. The results can be visualized in the 'Results' section as radial diagrams for three groups of nutrients: macronutrients, vitamins, and minerals. Figures 3 to 5 depict these results for a food product consisting of 100 g of tofu and 100 g of banana.



**Figure 3.** Macronutrient coverage by the product.



**Figure 4.** Vitamin coverage by the product.



**Figure 5.** Mineral coverage by the product.

## 4.2. Results of coupling HN-Assistant and GPT-4o

While HN-Assistant's quantitative analysis and data visualization capabilities are impressive, AI assistants like GPT-4o bring complementary skills to the table. These language models, trained on vast amounts of data, possess a wealth of knowledge spanning various domains, including nutrition, health, and wellness. They can provide in-depth explanations, contextual information, and evidence-based insights that enhance the understanding and practical application of the numerical data provided by HN-Assistant. A Python API is used to interact with GPT-4o.

Figure 6 presents the prompt passed to the LLM.

I will provide you the evaluation results using a proprietary software application for a male 58 years old, 1.69 cm tall, weighing 74 kg, with a moderate level of physical activity. You should comment the results and provide nutrition recommendations. The application also provides conclusions concerning how much a certain product covers certain nutrition requirements. I will provide the results of the evaluation of a food product with the main components, tofu and banana, 100 g each. The results are three radial diagrams. Comment about how good this product is for the person evaluated. Provide a conclusion up to 100 words long. The diagrams are as follows: {the diagrams}.

**Figure 6.** The prompt passed to the LLM.

Figures 7 and 8 illustrate the output generated by GPT-4o when information from the HN-Assistant is provided.

The evaluation indicates a BMI of 25.9, classifying as overweight. To manage weight, consider a balanced diet with a slight calorie deficit. Focus on whole foods, lean proteins, and plenty of vegetables to meet your macronutrient needs. Limit added sugars to 10g/day. Ensure adequate intake of fiber (32g) and essential vitamins and minerals, particularly Vitamin D (15mcg), Vitamin C (110mg), and calcium (950mg). Regular physical activity is beneficial, so maintain or increase your current level. Hydration and portion control are also key. Consulting a nutritionist for personalized advice could be advantageous.

**Figure 7.** The GPT-4o output concerning nutrition recommendations for the evaluated individual (by HN-Assistant).

The tofu and banana combination provides a balanced profile of macronutrients, with moderate protein and carbohydrate content. However, it falls short in covering vitamin needs, particularly Vitamin D, B12, and C. Mineral coverage is limited, especially in zinc and iron. This product can be a part of a balanced diet but should be complemented with other foods rich in essential vitamins and minerals to meet daily requirements. Including leafy greens, nuts, and fortified foods can help achieve a more comprehensive nutritional intake.

**Figure 8.** The GPT-4o output concerning the conclusion about the analyzed food product (by HN-Assistant).

As can be noticed from the prompt (Figure 6), the LLM was limited to providing short outputs (i.e., up to 100 words). This was done for brevity. When necessary, this limit can be modified.

#### 4. Discussion

Integrating HN-Assistant with multimodal language models like GPT-4o heralds a transformative era in personalized nutrition. This synergy merges precision in data-driven analysis with the adaptability and engagement of advanced language processing, offering a comprehensive approach to dietary management that can significantly enhance individual health outcomes.

By combining analytical capabilities with interpretative power, users receive not just raw data but also personalized, actionable insights. This integration allows for a nuanced understanding of nutritional needs, considering individual factors such as lifestyle, preferences, and health goals. For instance, when HN-Assistant identifies a deficiency in a particular nutrient, GPT-4o can suggest foods or meal plans tailored to the user's dietary habits and cultural context, leading to more effective dietary changes and improved adherence.

The interactive nature of GPT-4o enhances user engagement by providing explanations, answering questions, and adapting recommendations in real-time. This dialogue-based approach demystifies complex nutritional concepts, making them more accessible and less intimidating for users. As a result, individuals are more likely to understand and follow the guidance provided, leading to better health outcomes. Moreover, the system's ability to adapt to user feedback and changing circumstances ensures that the advice remains relevant and effective over time.

One standout feature is the capacity for real-time adaptation. As users input new data, the system can instantly adjust its recommendations, ensuring ongoing support that aligns with current needs and goals. Such adaptability is crucial in addressing the fluid nature of human health and lifestyle changes.

Despite its potential, the integration is not without challenges. Ensuring privacy and security of user data is critical, especially given the sensitivity of health-related information. Robust measures must protect against data breaches and unauthorized access. The system must also minimize biases and inaccuracies, which could lead to inappropriate recommendations. Continuous validation against current nutritional science is necessary to maintain credibility and reliability.

An additional way to improve the results of the integration would be adding a retrieval augmented generation (RAG) module. This supposes the creation of a vector database containing relevant information concerning nutritional aspects (e.g., based on information from credible sources like [1-3]) and supplementing the query passed to the LLM with the information from this database using semantic similarity [16-18].

As technology evolves, integrating data-driven applications with multimodal models will likely become more sophisticated [19-21]. Future iterations could incorporate additional data sources, such as biometric sensors or genetic information, to provide even more personalized and precise nutritional guidance. Expanding the system's capabilities to include mental health and wellness support could offer a holistic approach to health management.

## 5. Conclusions

The integration of HN-Assistant with multimodal language models like GPT-4o represents a significant advancement in personalized nutrition. By combining precise data analysis with adaptive, user-friendly communication, this approach has the potential to revolutionize dietary management, promote healthier lifestyles, and improve individual well-being. As we continue to refine and expand these technologies, their impact on public health and individual empowerment will grow, contributing to a healthier, more informed society.

**Conflicts of Interest:** The authors declare no conflict of interest.

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**Acknowledgements.** This work was supported by the National Agency for Research and Development (NARD) under the grant number 23.70105.5107.05 for the project Exploratory analysis of food security in the Republic of Moldova based on metrics of sustainable and nutritional quality (SNuQ) of food products, implemented at the Technical University of Moldova. We also acknowledge the support of the Technical University of Moldova through grant number 020405 for the project Optimizing food processing technologies in the context of the circular bioeconomy and climate change. We express our gratitude to all contributors and institutions involved in the successful execution of these research initiatives.

**Citation:** Iapăscuță, V.; Țurcanu, D.; Siminiuc, R. Integration of a data-driven software application and a multimodal LLM for enhanced nutritional guidance: a case study. *Journal of Engineering Science* 2024, XXXI (3), pp. 75-84. [https://doi.org/10.52326/jes.utm.2024.31\(3\).07](https://doi.org/10.52326/jes.utm.2024.31(3).07).

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