Kaunas University of Technology
Faculty of Mechanical Engineering and Design

Integration of Large Language Models into Digital Decision-support Systems for Improving Quality and Resource Efficiency in Food Manufacturing

Master's Final Degree Project

Rokas Žygimantas Palionis
Project author

Assoc. Prof. Dr. Laura Gegeckienė
Supervisor

Kaunas, 2026

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Industrial Engineering and Management (6211EX018)

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Assist. Prof. Pr. Darius Pauliukaitis

Reviewer

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Kaunas University of Technology
Faculty of Mechanical Engineering and Design
Rokas Žygimantas Palionis

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Task of the Master's Final Degree Project

Given to the student – Rokas Žygimantas Palionis

1. Title of the Project

Integration of Large Language Models into Digital Decision-support Systems for Improving Quality and Resource Efficiency in Food Manufacturing

(In English)

Didžiųjų kalbos modelių integravimas į skaitmenines sprendimų pagrindimo sistemas maisto gamyboje kokybės ir išteklių naudojimo efektyvumui didinti

(In Lithuanian)

2. Aim and Tasks of the Project

Aim: to integrate a large language model–assisted digital decision-support framework aimed at improving product quality, process efficiency, and resource utilization in industrial food manufacturing.

Tasks:

1. to analyze quality-critical formulation and process variables influencing sensory performance, stability, and production efficiency in selected food systems;
2. to design a structured LLM-assisted digital decision-support framework integrating formulation knowledge, process parameters, and quality indicators;
3. to apply the developed framework to generate improved formulation and process parameter scenarios under industrially relevant manufacturing conditions;
4. to experimentally validate selected scenarios through sensory evaluation and relevant quality assessment methods;
5. to evaluate the economic and managerial implications of LLM-assisted decision-support implementation, including its impact on resource consumption, waste reduction, production efficiency, and operational decision-making in food manufacturing.

3. Main Requirements and Conditions

Quality management requirements in accordance with ISO 22000:2018, HACCP principles, and relevant EU food legislation (Regulation (EC) No 178/2002 and Regulation (EC) No 852/2004). Application of the Large Language Model (LLM). Sensory evaluation according to ISO 13299:2016 guidelines.

4. Additional Requirements for the Project, Report and its Annexes

Non applicable

Project author	Rokas Žygimantas Palionis		02-03-2026
	(Name, Surname)	*(Signature)*	*(Date)*
Supervisor	Laura Gageckienė		02-03-2026
	(Name, Surname)	*(Signature)*	*(Date)*
Head of study field programs	Regita Bendikienė		02-03-2026
	(Name, Surname)	*(Signature)*	*(Date)*

Rokas Žygimantas Palionis Integration of Large Language Models into Digital Decision-support Systems for Improving Quality and Resource Efficiency in Food Manufacturing. Master's Final Degree Project, supervisor Assoc. Prof. Dr. Laura Gegeckienė; Faculty of Mechanical Engineering and Design, Kaunas University of Technology.

Study field and area (study field group): Production and Manufacturing Engineering (E10), Engineering Sciences (E).

Keywords: large language models; decision-support system; frozen yeast-raised bakery; product development; food quality improvement.

Kaunas, 2026. 89 p.

Summary

This project analyses the usage of the DSS based on large language models in the context of the food product development process in the food industry. As an object of analysis, a yeast-raised product "Lemon Curd Poppy Seed Loaf" is chosen, the present recipe and production of which does not provide the required level of quality stability during 6 months of frozen storage. The aim of the research is to implement an LLM-based DSS that would provide quality improvement and increase efficiency of food product development in the industry. In the theoretical part of the paper, Food Quality 4.0 and Food Processing 4.0 trends, application of LLMs for decision support, RAG and HITL approaches, and factors of deterioration of quality of frozen yeast-raised products: water migration, decrease in yeast activity, weakening of gluten structure, and formation of ice crystals are investigated. On the basis of theoretical analysis, a structure for creation of LLM-DSS is developed, considering recipe, process parameters, raw materials requirement, and quality criteria. In practice, the suggested system is used in three different scenarios - the control recipe (K0), modified recipe (S1), in which part of sugar is replaced with glucose syrup and inulin, while the amount of water is decreased, and modified recipe and process (S2), where part of the flour is replaced with wheat malt, the "CO2MMITTED BRIOCHE FREE 5%" improver content is increased, and proofing temperature is reduced. After four months of freezing, a sensory analysis and an ImageJ analysis of crumb structure were conducted. S1 received the highest score in sensory testing - 8,0 points, while S2 had the smallest area of structural objects in ImageJ – 56,4% relative to K0. Economical and managerial evaluation demonstrated that usage of LLM-DSS decreased the size of the decision search space up to 66,7%. According to this evaluation, recipe modification S1 is preferred as the most applicable option for further implementation due to its quality improvement and lack of necessity for process modifications.

Rokas Žygimantas Palionis. Didžiųjų kalbos modelių integravimas į skaitmenines sprendimų pagrindimo sistemas maisto gamyboje kokybės ir išteklių naudojimo efektyvumui didinti. Magistro baigiamasis projektas, vadovė doc. dr. Laura Gegeckienė; Kauno technologijos universitetas, Mechanikos inžinerijos ir dizaino fakultetas.

Studijų kryptis ir sritis (studijų krypčių grupė): Gamybos inžinerija (E10), Inžinerijos mokslai (E).

Reikšminiai žodžiai: didieji kalbos modeliai; sprendimų pagrindimo sistema; šaldyti mieliniai kepiniai; produktų vystymas; maisto kokybės gerinimas.

Kaunas, 2026. 89 p.

Santrauka

Šiame darbe analizuojamas didžiųjų kalbos modelių pagrindu veikiančių sprendimų priėmimo sistemų (DSS) naudojimas maisto pramonės produktų kūrimo procese. Analizės objektu pasirinktas mielinis produktas „Lemon Curd Poppy Seed Loaf“, kurio dabartinis receptas ir gamybos procesas neužtikrina reikiamo kokybės stabilumo lygio laikant 6 mėnesius šaltyje. Tyrimo tikslas - įdiegti LLM pagrįstą DSS, kuris užtikrintų kokybės gerinimą ir padidintų maisto produktų kūrimo efektyvumą pramonėje. Straipsnio teorinėje dalyje tiriamos „Maisto kokybė 4.0“ ir „Maisto perdirbimas 4.0“ tendencijos, LLM taikymas sprendimų priėmimo palaikymui, RAG ir HITL metodai bei šaldytų mielinių produktų kokybės blogėjimo veiksniai: vandens migracija, mielių aktyvumo sumažėjimas, glitimo struktūros susilpnėjimas ir ledo kristalų susidarymas. Remiantis teorine analize, atsižvelgiant į receptūrą, proceso parametrus, žaliavų poreikį ir kokybės kriterijus, sukurta LLM-DSS kūrimo struktūra. Praktikoje siūloma sistema taikoma trijuose skirtinguose scenarijuose: kontrolinėje receptūroje (K0), modifikuotoje receptūroje (S1), kurioje dalis cukraus pakeista gliukozės sirupu ir inulinu, o vandens kiekis sumažintas, bei modifikuotoje receptūroje ir procese (S2), kur dalis miltų pakeista kvietiniu salyklu, padidinamas „CO2MMITTED BRIOCHE FREE 5 %“ pagerintojo kiekis ir sumažinama kildinimo temperatūra. Po keturių mėnesių šaldymo buvo atlikta juslinė analizė ir ImageJ analizė, skirta minkštimo struktūrai įvertinti. S1 gavo aukščiausią balą juslinėje analizėje - 8,0 balus, o S2 turėjo mažiausią struktūrinių objektų plotą ImageJ analizėje - 56,4 % palyginti su K0. Ekonominis ir vadybinis vertinimas parodė, kad LLM-DSS naudojimas sumažino sprendimų paieškos erdvę 66,7 %. Remiantis šiuo vertinimu, receptūros modifikacija S1 yra tinkamiausias variantas tolesniam įgyvendinimui dėl kokybės pagerėjimo ir procesų modifikavimo nebūvimo.

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List of Abbreviations and Terms

Abbreviations:

AI – Artificial Intelligence;
AI RMF – Artificial Intelligence Risk Management Framework;
CAPA – Corrective and Preventive Actions;
DSS – Decision-Support System;
DOE – Design of Experiments;
ERP – Enterprise Resource Planning;
EU – European Union;
FMEA – Failure Mode and Effects Analysis;
GMP – Good Manufacturing Practice;
HACCP – Hazard Analysis and Critical Control Points;
IoT – Internet of Things;
KPI – Key Performance Indicator;
LLM – Large Language Model;
MES – Manufacturing Execution System;
QMS – Quality Management System;
RAG – Retrieval-Augmented Generation;
RLHF – Reinforcement Learning from Human Feedback;
SOP – Standard Operating Procedure;

Introduction

Modern industrial food production is increasingly facing situations where quality problems of products cannot be solved with recipe and processing parameter tuning alone. Such situation occurs in the area of frozen yeast-raised baked goods where final quality is influenced by recipe, functionality of raw materials, proofing, freezing, storage and baking. Possible quality problems in such products can be connected to reduced softness, lower moisture perception, non-homogenous structure, weaker structure, or worse consumer acceptance. As a result, quality assurance involves not only laboratory monitoring but also difficulties in decision making in product development.

The relevance of this research rises from the fact that product development in the food industry occurs in the environment of high uncertainty. When developing a new product or changing the current recipe, technologist should consider the composition and price of raw materials, their functionality, technological parameters, available equipment, consumer needs and requirements, labelling, shelf-life, and consumer acceptability. In practice, this means multiple trial-and-error cycles involving the adjustment of either recipe, production parameters, or both. Every trial requires certain amount of raw materials, time on production lines, labour, energy and freezing capacity.

Thus, product development efficiency directly depends on the ability to fast and reasonably narrow the scope of possible solution. At the same time, it is very important to consider the approach known as Food Quality 4.0 and Food Processing 4.0. It implies that QMA in the modern environment supposes information integration, digitization of processes, faster decision making and resource saving. LLM's may find practical applications when technologists develop new food products since such models allow the combination of different types of information like recipe, technological parameters, characteristics of raw materials, scientific literature, quality metrics, and experts' conclusions.

However, it is necessary to point out that such models cannot be used independently as decision-makers. In food production their value arises from integrating these models in a well-designed DSS. The novelty of this project is related to integration of a digital DSS based on LLMs not in recipe modelling but in a specific practical example of product development in the food industry. The current recipe and technological process of chosen product do not provide sufficient quality stability over the required 6 months of frozen storage period. LLM model is used to generate possible scenarios, formulate arguments and develop solutions, whereas selected scenarios are verified in practice via sensory analysis and crumb structure analysis with ImageJ. In other words, the problem posed in this project is how to rationally adjust recipe and technological process during product development in order to ensure higher quality stability of frozen yeast-raised baked good. Research objective is the integration of a digital LLM-DSS to improve frozen yeast-raised baked good recipe and technological process.

Practical application of the proposed scenarios will allow us to make product development more efficient in terms of faster decision making, reduced number of trials, more rational management of raw materials and technological parameters, lower probability of defects and clear understanding of the relations between technological decisions and final product quality.

Aim: to integrate a large language model–assisted digital decision-support framework aimed at improving product quality, process efficiency, and resource utilization in industrial food manufacturing.

Tasks:

1. to analyse quality-critical formulation and process variables influencing sensory performance, stability, and production efficiency in selected food systems;
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5. to evaluate the economic and managerial implications of LLM-assisted decision-support implementation, including its impact on resource consumption, waste reduction, production efficiency, and operational decision-making in food manufacturing.

Hypothesis: the integration of Large Language Models into digital decision-support systems in food manufacturing enables more effective formulation and process parameter decisions, resulting in improved product quality, enhanced process efficiency, and more efficient resource utilization compared to traditional expert-driven approaches.

1. The Relevance, Theoretical Foundations and Integration Logic of Applying an LLM-Based Decision Support System in Food Production

1.1. Background of The Problem: Quality and Resources Usage Efficiency Dilemma in Food Manufacturing

The production process in the industrial food sector exists in a complex sphere of compromises between such factors as sensory quality (taste, smell, texture), technological stability (such as maintaining structure after freeze-thaw processes), food safety, and process efficiency. Making decisions in the production cannot be limited by only following the formulation since there will always be uncertainties as variations in raw material quality, process parameters (mixing, fermenting, freezing, storing), status of the equipment, actions of workers, etc.

Under such conditions, quality assurance becomes both the problem of laboratory work and of a socio-technical problem where the quality of the decision-making process itself is casual upon the capacity of the organisation to combine all available data, technological expertise, and procedural rules into a practical decision support system. Here, resource efficiency is understood in much wider terms, including not just expenses on energy or raw materials, but also reduction of waste and defects, reducing variations, preventing overheating or overcooling, efficient cold storage practices, and the time of decision-making.

It is important to emphasize that decisions in the food industry must comply with mandatory food safety and hygiene provisions laid down in EU regulations, which establish general principles of food law and safety requirements [1], as well as hygiene rules for food handling activities [2]. In addition, structured management systems (e.g., ISO 22000) are widely implemented in companies, which formally describe how risks and processes are managed, but do not in themselves automate the quality of decisions if the information remains fragmented and inaccessible to production staff. Therefore, digital decision support systems (DSS) are becoming a practical bridge between regulations, standards, technological expertise, and real-time production decisions.

Large language models (LLMs) are relevant to this topic not as just another analytical tool, but as a new type of interface between humans, documented knowledge, and data. LLMs can act as a natural language layer capable of transforming information in various formats (specifications, technical instructions, quality protocols, HACCP documents, raw material certificates, laboratory results, MES/SCADA records) into actionable recommendations. However, scientific literature emphasizes that the integration of LLM into socio-technical systems poses complex challenges - from bias and privacy to responsibility, reliability, and unexpected uses, and especially overconfidence in "human-sounding" responses [3]. For these reasons, the application of LLM in food production must be based on clear architectural solutions (e.g., retrieval-augmented generation), human oversight mechanisms (human-in-the-loop), and validation logic so that decisions are not only smart but also traceable, verifiable, and consistent with quality management requirements [3].

1.2. Key Terms and Operational Meaning of The Project

In the context of this project, it is important to separate and define exactly what will be considered in practical applications, in engineering and managerial practices. Within the framework of this project, a DSS is counted as a system of algorithms, information resources and interfaces designed to assist in the decision-making process by giving recommendations, scenarios, or insights based on available data and organizational expertise. Quality, in the food production context, should be understood as an indicator including both sensory characteristics (certain degrees of crispy, tender, aromatic), physical-chemical parameters (humidity, acidity, texture-related), safety criteria (microbiological safety, meeting certain requirements or restrictions) and customer expectations.

Resource efficiency in the project means achieving a desired degree of quality at lower cost or losses: less raw materials wasted, fewer rejects, less energy spent per unit, less machine downtime, higher process stability statistics, less variation in any other sense. LLM-assisted DSS refers to the fact that the LLM is not supposed to act as an independent decision-maker but serve as an auxiliary system able to interpret the context, find and assemble required information, build possible scenarios and make recommendations with reasoning that traces its sources with the final decision made by a human.

Another crucial term is RAG or retrieval-augmented generation. According to the literature, it is a technique that involves combining an information retrieval component with LLM generation so that the answer becomes based on specific data from the main information source, thereby avoiding potential hallucinations [4]. For example, it is stated that in the case of clinical decision support, RAG technique uses a retriever module that extracts relevant information from the knowledge base in addition to answering the query by an LLM, thus significantly reducing the chance of generating information not relevant to the domain and ensuring higher accuracy [4]. Although such technique belongs to medicine and healthcare in general, it is easy to see how it may be directly applied to food manufacturing with knowledge bases being made of company-specific technical instructions, allergens management procedures, recipe history, protocols in the laboratory, equipment specifications, etc.

Human-in-the-loop, as another key concept, is discussed in relation to socio-technical systems and defined as a crucial principle, according to which humans are expected to be involved throughout the process of decision-making from designing to usage, with their feedback taken into account to reduce risks and increase accountability [5]. In food production, LLM recommendations should be confirmed by technologists or quality managers, while decision-making scenarios proposed by the system should be thoroughly explained and audited.

1.3. Large Language Models: Technological Developments and Features Important for Industrial Decision Support

LLM technology is based on retrieving architecture, which has become the backbone of large-scale language models since 2017. LLMs are trained using the self-supervised principle from massive amounts of data and are then adapted to domains through fine-tuning, instruction adaptation, and RLHF (reinforcement learning from human feedback) methods like shown in Fig. 1. The literature showcases that in-context learning, instruction tuning, and RLHF have led to a significant leap in capabilities and expanded the spectrum of logical relations, highlighting the potential of multimodal large models (text, images, sound, time series) in industry [6].

Such multipurpose dimension is particularly relevant in food production, as quality assessment often depends on visual data (e.g., porosity structure, colour, baking uniformity) and sensitive parameters (temperature, humidity, pressure, energy consumption). Thus, LLM integration should not be reduced to a “text assistant”; the real potential arises when LLM acts as an orchestrator, combining various analytical components and providing the decision maker with a unified interpretation.

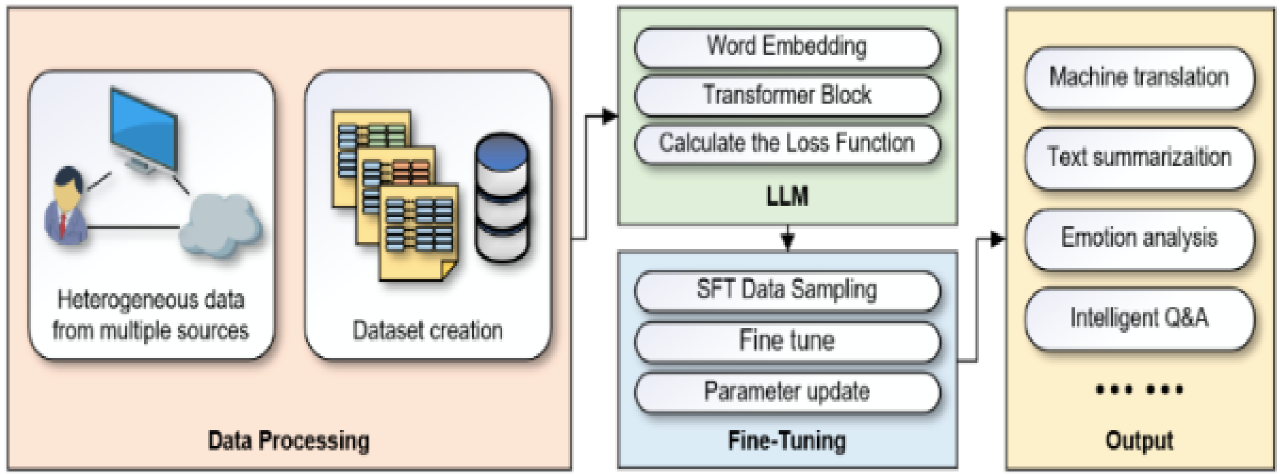

Fig. 1. Architecture and Training Stages of Large Language Models

At the same time, the literature points to very important limitations that become critical in industry. First, LLMs tend to hallucinate - generate conclusions that sound convincing but are actually unreal, so generative functions alone are not enough, knowledge must be filtered through RAG or structured data [4]. Second, LLMs are generalists, trained on broad and diverse content, so context recognition in a specific organization and liability issues become more complex than in the case of traditional, narrowly trained models [7]. Third, a human response style can lead to overconfidence, which is particularly dangerous in high-risk processes where decisions have a direct impact on safety, quality, and costs [7]. For these reasons, academic discussions on LLM industrial solutions focus not on autonomy, but on reliability architectures, auditing, supervision, clear roles and continuous evaluation.

1.4. Integration of LLM Into Digital Decision Support Systems: Architecture, Data Layers, and Control Logic

Modern LLM-assisted DSS architecture is almost always composite, LLM becomes the top layer of the interface and reasoning, while the actual analysis, rules and calculations are performed by other systems. Digital manufacturing literature shows that LLM can contribute to process automation, planning, model creation, and complex manufacturing process management, reducing human error and increasing operational efficiency [8]. However, such solutions require the integration of LLM with structural information systems (MES, QMS, ERP, laboratory LIMS), data engineering (ETL, semantic search), and quality assurance mechanisms (traceability, audit trail).

For example, the digital manufacturing review identifies application areas that cover quality control through advanced retrieval-augmented generation systems, FMEA analysis improvement, and the use of LLM agents in modular manufacturing systems [8]. These areas correlate directly with food production needs where process deviations and failure modes (e.g., dough mixing, insufficient fermentation, uneven freezing) often have clear causes that can be described by FMEA logic, and quality control decisions can be supported by documentation and sensor data.

The RAG mechanism is particularly important for two reasons: first, it allows grounding the response with specific company documents or data, second, it provides traceability, which is essential in quality systems and audits. Clinical DSS literature emphasizes that the additional context provided by RAG reduces hallucinations and allows for more informed, domain-specific responses [4]. Similarly, in food production, RAG can include recipe version history, technological modes, raw material COAs, descriptions of critical control points, allergen management procedures, and laboratory testing methodologies. The practical logic is - the user asks a question ("why does this batch have lower volume retention after thawing?"), the system pulls up related process logs and recipe changes, and the LLM formulates hypotheses, suggests checks, and presents scenarios with clear evidence. However, research on socio-technical systems warns that even with technical measures, organizational discipline is necessary for regular audits, privacy protection measures, inclusive data management, and clearly defined responsibility for errors are required [7]. Therefore, LLM-assisted DSS in food production must be designed as a controlled, audited system, rather than a "free chatbot."

1.5. Applications in The Food Industry: From Recipe Scenarios to Process Parameters and Quality Control

Within the process of food product development and production, the decision support problems are divided into two main classes: recipe (formulation) and process (production modes). The first category is characterized by the fact that the complexity of the effect of raw materials and functional ingredients on sensory and stabilizing characteristics is very high and does not admit any deterministic description. In turn, at the process level, solution difficulty consists in the necessity of controlling variation, since even the correct recipe may produce suboptimal result due to deviations from a relatively narrow stability zone in terms of mixing energy, fermentation time, cooling schedule, etc. Hence, LLM incorporation into DSS should aim at scenario generation and selection in such a way that the system would suggest feasible combination of recipe and process parameters that would increase the probability of target quality achievement at reduced costs.

As for the digital manufacturing practice, there is a significant amount of sources stating that LLMs have been effectively employed in process management and automation, planning, and quality control solutions using the RAG architecture and structured data integration [8]. In the context of food technology, this translates to the natural language interface to MES/QMS systems which could help technologists to detect reasons behind quality problems, compare batches, identify parameter changes, and implement corrective actions.

Another critical aspect of LLM-based decision support is related to quality indicators and their automation. Indeed, such approach may be beneficial for the research and, hence, can be incorporated as part of the decision-making algorithm. For instance, previous research by Rokas Žygimantas Palionis was devoted to frozen bakery products and involved typical industrial procedure including dough mixing, product shaping, shock freezing, storage at -18 °C, thawing, and baking. Quality assessment was done with the help of sensory evaluation and crumb image analysis performed with ImageJ software [9]. This kind of methodology is highly relevant for this master's thesis because, apart from LLM-generated scenarios, a researcher would need to test them in laboratory or pilot conditions using both sensory and instrumental approaches.

Moreover, sensory analysis itself is standardized within ISO documents (ISO 13299 among others), so that DSS can use not only the company-specific information but also internationally acknowledged methodology in order to improve credibility and validity of the research [10]. Thus, we can assert that LLM-based DSS is not a "black box" but rather a tool embedded into classical quality approach: hypothesis → scenario → testing → evaluation → improvement.

1.6. Formulation Variables that Determine Quality in Food Systems and their Impact on Selected Product Characteristics

Besides the composition of ingredients used as the raw material, the quality of the final product depends on rather particular aspects associated with the ratio between various ingredients, the specific purpose for which they are used, their functional interactions, and changes in the properties of ingredients during production. Formulation should thus be seen not as a recipe, but as a set of quality control variables that determine the properties of a product -its textural properties, structure, water movement, oxidization, durability, and sensory characteristics -in advance. In the AI overview of agri-food systems, the need to control quality, sensory properties, and shelf life becomes more acute, which, in turn, makes the use of AI approaches highly relevant due to their capacity to control multidimensional interactions [13].

Moreover, formulation-related variables rarely work individually in the food industry: moisture binders influence not only textural properties, but also the process of thermal processing; the ratio of protein and starch influences not only structure and product yield, but also mouthfeel and the product's susceptibility to oxidization; fat content influences mouthfeel, as well as the product's stability; the type and content of sugars, in addition to sweetness, influence not only water activity, but also glass transition temperature and freeze-thaw stability. That is why the problem of product formulation is increasingly moving from being solved through intuition and technology to formulated decisions based on models, which evaluate not one parameter, but a number of quality parameters at once. According to recent reviews of food quality management, in the era of Quality 4.0, quality functions require the development of digital solutions that facilitate simultaneous integration of product design, process information, and quality outcomes [14].

These solutions are especially required for the creation of products where quality is highly susceptible to small changes in composition: baked goods, fermented products, dairy systems, and dried products, among others. This makes it essential to understand quality-critical formulation variables as controllable input parameters, the influence of which on selected parameters should not only be defined but also analysed in a decision support system.

The ability to create food systems that maintain their quality despite variations in raw materials should be emphasized as particularly important in the case of product formulations because, in the industrial setting, recipe execution occurs far from ideal. In addition, ingredients can vary greatly depending on the type of matrix, since the same hydrocolloid will have a different effect on the properties of milk and frozen dough; similarly, proteins may exhibit significantly different characteristics depending on pH, the content of salts and water, and thermal processing. The review of AI applications in agri-food systems indicates that modelling such multifunctional relationships becomes increasingly important in the industry due to the insufficiency of single-factor experiments for meeting demands for speed and economic efficiency [13].

In this context, it is necessary to separate ingredient quantity from its function, e.g., an emulsifier or cryoprotectant may be important because of its high impact on the structural stability of the product or its shelf life. This point is in line with the idea behind the project that was previously conducted by Rokas Žygimantas Palionis on the topic of frozen baked goods [9], showing that minor formulation changes may lead to drastic textural changes. This aspect needs to be taken into account during theoretical analysis of the problem, emphasizing the necessity to assess formulation variables defining quality as not just individual recipe elements, but controllable quality levers that can be predicted and interpreted in AI and LLM-supported decision support systems [13, 14]. Such argument supports this work as a whole because the proposed system should not only generate recipe, but also justify why certain combinations of ingredients can be expected to increase certain product characteristics.

1.7. Process Variables that Determine Quality in Food Production and their Relationship to Structural, Sensory, and Functional Properties

In addition to proper design, there should be accurate process control as well for consistent results in food quality analysis. In terms of quality management of food systems, process parameters play a role as critical as those related to formulation. Reviewing the concept of digital twins in food processing shows that there is high potential in the use of real-time simulation and control in the food industry in the context of products that are especially sensitive to the process footprint. Thermal processing, drying, freezing, and cold chains are typical examples of operations where real-time simulation and management of process parameters become crucial for maintaining the required quality [15]. Process footprint encompasses many aspects, including temperature, time, energy consumption, rate of moisture removal, mechanical load, and shape of curves of cooling or freezing. The process footprint shapes quality results as much as the composition itself.

There is an abundance of examples in food production where the same composition and an exact recipe can lead to entirely different quality depending on process dynamics: over-fermentation, rapid surface drying, inefficient cooling, unstable freezing conditions, non-uniform heat distribution, or variable mechanical load may lead to different quality outcomes. That is the reason why, in the framework of quality assurance theory, process variables should be considered quality critical and control of which will be the determining factor not only for the technical requirements but also for consumers' experience, yield, and loss of product. Process parameters play a significant role for quality when the changes in the structure occur. For instance, temperature, air velocity, and duration have a direct effect on the amount of residual moisture, texture, colour, and nutrient content in drying processes.

As seen in recent reviews of AI solutions, neural networks and models capable of predicting quality based on process signals are widely applied in such operations [13]. In the case of LLM-assisted decision-support system, it is also important because, although LLM itself does not simulate the process, it can be the explanatory layer in the process of establishing a link between parameters' values and their influence on the product's properties. Additionally, digital twins allow simulating the scenarios of changing process variables before applying them [15].

This shows that supporting decision-making in food production should go beyond generating recipes and cover process parameter management. After all, these variables' interaction with raw materials determines certain characteristics of the product like texture, colour homogeneity, volumetric properties, porosity, crispness, moisture migration, or oxidative stability. Thus, extending the scope of research from artificial intelligence technologies to food industry issues opens up a new question of how process variation should be managed to improve efficiency and save resources.

The management of process variables is also important for resource efficiency because such variation leads to increased expenses and inefficiencies. Energy inefficiency, unnecessarily long baking or drying periods, problems during the cooling phase, or poor freezing conditions all result in higher unit cost, higher energy efficiency, and increased risk of product defects. Recent reviews of the AI's applications in food safety and quality show that, by improving monitoring capabilities, predictive analytics, risk identification, and management of processes, AI can greatly improve the efficiency of operations in the food industry.

However, the main issues remain the immaturity of the digital infrastructure, data standardization problems, and regulatory barriers [16]. It is significant in this context because it supports the idea about the necessity of process parameter control as a key lever for improving resource efficiency. While, on the one hand, it is possible to argue that the efficiency increases due to the presence of LLM, on the other hand, it is the fact that DSS is able to manage process parameters through linking quality and cost metrics. Thus, process parameters are not simply operational values to watch on screens, but variables to control.

1.8. AI, LLM, and Quality 4.0 in the Food Industry: A Broader Perspective from Quality Control to the Orchestration of Digital Solutions

It is necessary to widen the horizon for the correct use of the LLM within the framework of the food production industry beyond the limits of the narrow concept of language modelling and consider AI technologies as a constituent element of Quality 4.0 transition. As shown by the recent studies devoted to food quality management and management practices, the incorporation of technologies of Industry 4.0 into the food production chain leads to fundamental changes in quality-related activities due to a transition from control to prediction and adaptability [14]. It implies that AI includes such elements as computer vision, sensor analytics, machine learning algorithms, digital twins, blockchain technologies, data analytics, as well as advanced UI/UX designs.

For this reason, it is more appropriate to perceive LLM as one of the orchestration technologies that are capable of helping explain, integrate, and communicate results generated by other analytical modules rather than being an independent source of solutions. This is especially important for the food sector since most quality issues related to food production are interdisciplinary because they touch upon the recipe, process, availability of ingredients, cleanliness, packing, and consumers' preferences. In the Quality 4.0 paradigm, LLM will become exactly that element that will help people move around these spheres of activity and prevent informational isolation.

Reviews of current applications of AI in the food industry prove that AI technologies are already widely applied in a variety of food manufacturing subsectors ranging from baking to dairy production and including beverages, fruits and vegetable processing, as well as packaging and sorting operations while the main objective is still improvement of quality, prolongation of shelf life, minimization of losses, and ensuring stability [13]. That is how theoretically, the application of LLM as a part of DSS is considered a natural continuation of the overall application of AI technologies within the food industry.

Nonetheless, it is vital to highlight that the use of LLMs contributes to solving problems that are challenging for traditional models since LLM allows interpreting nonstructured data and explaining the rationale of decisions. An overview of AI applications related to food quality and safety highlights that the role of AI extends far beyond the control of quality and encompasses such aspects as traceability, optimization of processes, predictive analytics, and quick response to risks [16]. Thus, taking into account all the above, it is possible to state that LLMs in food production are essential tools that contribute to the transition from reactive to proactive quality control and management.

1.9. Risks, Reliability and Socio-Technical Integration: Why Technology Alone is Not Enough

The implementation of LLM in industrial decision support systems inevitably changes decision-making practices within an organization, so risks must be assessed not only at the technical level, but also at the socio-technical level. The literature on socio-technical systems emphasizes that LLM integration poses complex challenges shown in Fig. 3. due to the interaction between social structures, human behaviour, and technological innovation, and therefore proposed human-centred integration focused on ethics, privacy, IP and unforeseen consequences [3]. The authors identify principles such as human-in-the-loop in Fig 2., longitudinal studies, proactive information campaigns, and regular audits to create ethically sound and adaptable solutions [3].

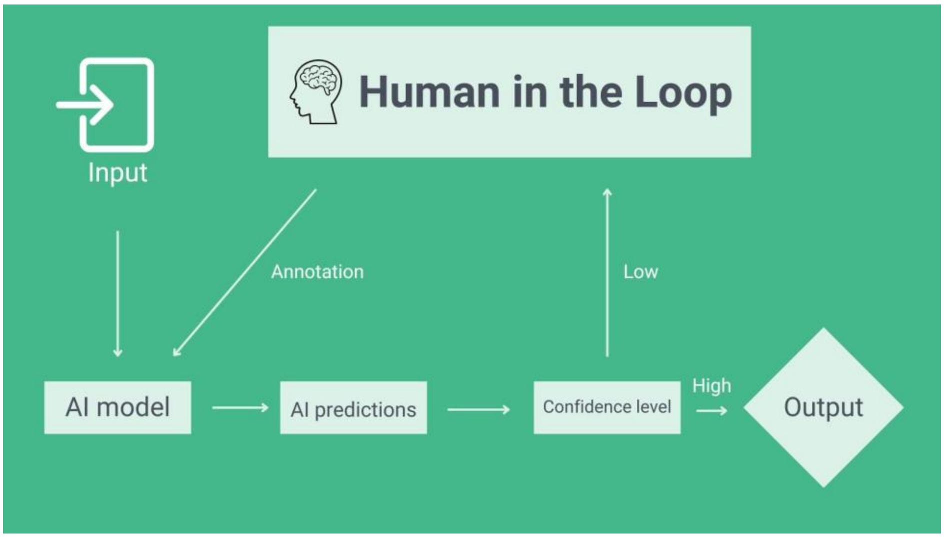

Fig. 2. Human-in-the-Loop AI Framework

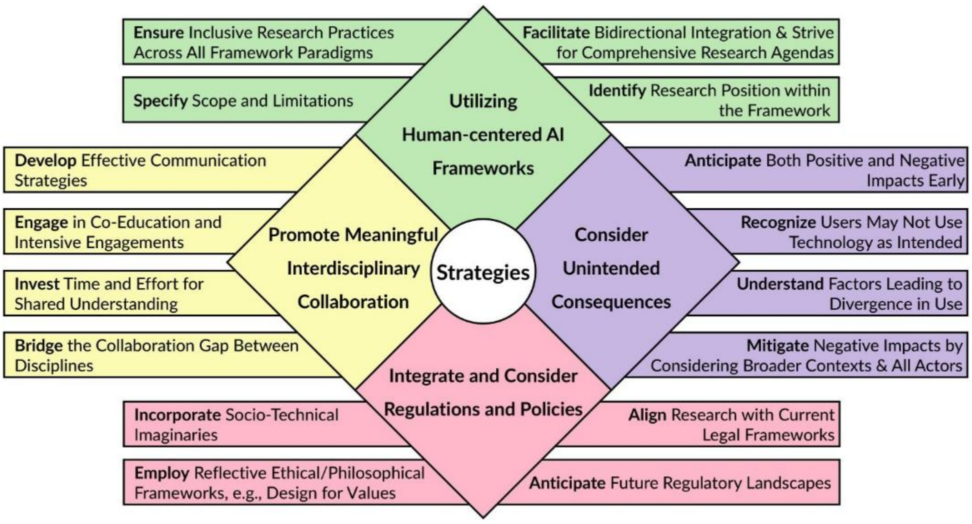

Fig. 3. Model of LLM Integration Into Socio-Technical Systems Interactions (according to Torkamaan et al., 2024)

In the food industry, this means that even a well-functioning prototype must have clear limits of use - in which situations does the system provide recommendations, in which does it only provide information, and when is the approval of technologists or the decision of a quality manager mandatory? It is also necessary to define how responsibility for incorrect recommendations will be managed, especially when they may have consequences for safety, traceability, or consumer confidence.

The issue of reliability is particularly well illustrated in the high-risk area of clinical decision support, where empirical evidence shows that LLM cannot replace specialists in independent complex decision-making, but has potential as an auxiliary tool that provides insights and information if integration is based on testing, continuous evaluation, and clear roles in the workflow [11]. More importantly, the RAG method is presented here as a means of reducing "hallucinations" and increasing domain specificity by incorporating the context of an external knowledge base into the response [4].

This analogy to food production is methodologically significant because if we want DSS to be reliable, we need to create a layer of evidence for quality, in which each recommendation is based on documents, data, or verifiable criteria. In other words, LLM should not decide, it should argue - present a cause and effect chain based on specific data and clearly indicate uncertainty. This allows innovation to be reconciled with a culture of quality, where decisions must be traceable and auditable.

1.10. Assumptions for Data and Knowledge Management in LLM-Assisted Decision Support: Documented Knowledge, Interoperability and Semantic Consistency

The deployment of LLM-DSS in food production mainly hangs on whether the company has managed to create an operational data and knowledge management system where documented procedures, different recipe variations, quality management systems, and production data are always the same and it is reachable. In the literature about digital manufacturing it is seen that LLM becomes more helpful in such operations only when models are connected to sources of information. Also it is important that it is made possible for them to access that information and interpret it to minimize errors and improve decision-making [12].

For food companies, knowledge tends to be distributed and requirements for production processes may vary from being contained in SOP documents to being in QMS or even being in the heads of technologists, equipment logs, or laboratory protocols. Knowledge distribution leads to decisions being made based on the capabilities of a certain individual to find out information and build up context, thus leading to inconsistencies in the process of decision-making depending on different shifts. LLM as a natural language interface may help lighten the issue only if a knowledge base is built on structured data.

The review additionally highlights that LLM contributes to improving compatibility and integration of information within various systems through translation of terminologies used by different sources into a common well formed space [12]. In food manufacturing, one and the same phenomenon (such as a small volume, an insufficient dough rise, and low porosity) will be named differently in technology, quality control and sales. DSS should be able to bring together all these phrasal variations to form a consistent diagnosis. It is then legitimate to claim that LLM- DSS has to be created along with documented hygiene and data management policies (versioning of recipe documents and standard operating procedures, data dictionary, common units of measure, relations between batch numbers, process parameters and quality characteristics). This proves that LLM-based artificial intelligence should be built on corporate knowledge management practices.

1.11. The Problem of Relevance and Traceability: RAG as a Mechanism for Ensuring the Reliability and Continuous Updating of Decisions

In a production food environment, the value of decision support decreases if the system cannot guarantee the relevance of information, as real process parameters, raw material variations, and internal procedures change more frequently than classic model update cycles. Clinical decision support studies emphasize that the reliability of LLM decisions in high-risk environments must be reinforced with additional mechanisms, one of the most important being retrieval-augmented generation (RAG), which allows responses to be generated based on an external knowledge base, thereby reducing the risk of hallucinations [4]. This principle is directly applicable in the food industry, as many decisions must be supported by evidence - descriptions of critical points, specifications, audit conclusions, descriptions of laboratory methods, etc. An overview of digital manufacturing shows that the application of LLM in quality control is increasingly based on advanced RAG architectures, which allow the model's response to be linked to specific documents and data, thus improving the validity and applicability of decisions [12]. In this way, DSS becomes not a response generator but a system of explanations that provides: a recommendation, its justification, references to sources, and limits of uncertainty.

In food production, this is critical for traceability because if a scenario changes a recipe or process parameters, it must be clear which document or data record was used as a basis and whether the decision is consistent with the company's QMS logic. RAG also solves the problem of outdated knowledge - when an SOP or specification is updated, the indexed knowledge base automatically changes the context of LLM responses, allowing the DSS to remain alive without constant model retraining. It is worth emphasizing that RAG in food production helps to manage not only the accuracy of information, but also organizational responsibility, as recommendations become auditable and consistent with quality requirements. This argument effectively combines the technical part of this work (LLM architecture) with the quality and management dimension (traceability, audit, responsibility).

1.12. Economic and Managerial Implications: How LLM-Assisted DSS Can Create Value and How to Justify It

to make this project economically and managerially significant apart from being a technological one, it is vital to define what kind of value DSS creates for the company and how to measure this value. The possible areas of integration of DSS with LLM technology, providing the opportunities for improvement of economical performance can be seen in Fig. 4. Literature on the subject states that LLM technology can increase efficiency due to its ability to help reduce human error and control complex processes [8]. Economic value has to be translated into indicators like rate of defects produced, hours spent on rework, amount of energy consumed per unit of production, raw materials wasted, machine downtime, NCRs, CAPA cycle duration and time taken to make crucial decisions. In terms of evaluation, it can be said that an effective method would be a before vs. after approach and scenario analysis - if the system manages to ensure stabilization of production processes and minimize variance, then the resulting low dispersion of scrap rates and waste reduction would directly lead to financial savings.

Also, indirect costs savings can be calculated based on reduced number of customer complaints, return risks, audit failures and traceability improvement, which is especially important when it comes to EU regulations [1-2]. As for managerial considerations, it could be stated that use of DSS with LLM as a technology is an effective way of operationalizing knowledge that decreases the dependence on expertise of particular specialists and facilitates standardization of decision-making practice among different shifts.

On the other hand, as far as socio-technical analysis is concerned, one has to admit that the integration of technologies implies certain expenditures on such activities as data cleansing and structuring, disciplined updates of documents, handling of privacy and intellectual property issues, training and auditing [7]. Therefore, a well-planned implementation should be based on TCO and ROI logic - that means that implementation cost, operational expenditure and benefits should be assessed over a specific period of time.

It is vitally important to understand the benefits not abstractly but according to the indicator-based data that will be obtained as the result of experiments and implementation of the scenarios generated with the help of DSS that improves quality. It is also necessary to prove experimentally that scenarios created by DSS do actually improve the sensory quality and reduce the amount of waste produced. The current project design has already been built up on a solid methodological ground - scenario generation and laboratory verification in sensory/technological terms, so all that is needed is to create an economic/managerial one.

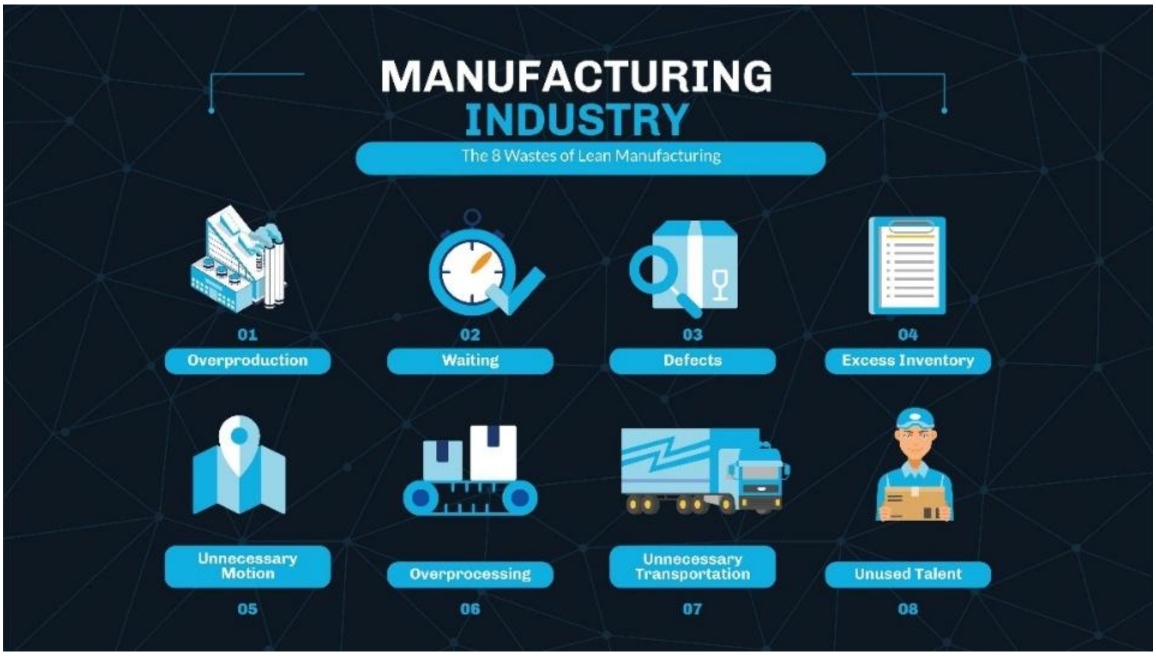

Fig. 4. Possible Fields for LLM DSS Integration Economical Improvements

1.13. Chapter Summary

A review of the literature indicates that the integration of large language models (LLMs) into decision support systems (DSS) is a promising direction, but its effectiveness depends on integration into a robust architecture that ensures the validity and traceability of information and reduces the risk of hallucinations by applying RAG principles and integrating data layers [4, 8]. Research on digital manufacturing provides practical application areas, such as improving quality control, refining FMEA methods, applying digital twins, and natural language interfaces with manufacturing systems [8]. At the same time, research on socio-technical systems emphasizes that technological solutions alone are insufficient—mechanisms for human-in-the-loop, auditing, data management, and accountability are necessary [3, 7]. Research on clinical decision support further indicates that LLMs should be used as auxiliary tools requiring continuous evaluation and clearly defined application boundaries [11].

In the context of the food industry, DSSs must be aligned with regulatory requirements (general principles of food law and hygiene standards) [1, 2] and quality assessment methodologies, including sensory analysis [10]. Furthermore, the literature indicates that product quality is determined by complex interactions between formulation variables (ingredient composition, functionality) and process variables (temperature, time, technological conditions), which directly affect sensory properties, stability, and production efficiency [13, 16]. Therefore, effective DSSs must be capable of integrating these multidimensional relationships and interpreting them.

From the literature it is possible to see that an LLM-based DSS should be developed as an auditable, human-supervised, and data-driven system for explaining decisions, rather than as a fully automated decision-making tool. The value of the system is revealed when it is capable of generating practically applicable formulation and process scenarios, the effectiveness of which is confirmed by experimental studies and evaluated according to indicators of quality, resource utilization, and operational efficiency.

2. Decision-Making Rationale in Food Production: From Theoretical Assumptions to the Application of LLM

This chapter seeks to present not only an overview of the existing technological conditions but also a theoretical justification for the approach to solving the problem, chosen in this work. The use of LLMs as a part of a digital decision support system, oriented towards optimizing food production technologies in terms of product quality and efficient resource use -all this becomes particularly important not just due to its novelty but due to clear technological and managerial logic. The point is that demonstrating relevance and scientific grounding of a certain approach to solving a complex problem is an essential part of a thesis and it is crucial for the success of further research. Thus, in addition to substantiating the complexity and importance of the problem, the theoretical justification will serve another purpose, i.e. it will show why the choice of the LLMs-based DSS direction makes sense and appears justified and potentially useful [3, 8, 16, 17], [20-22].

The specificity of food production is defined by the presence of multiple goals that should be accomplished, among them the achievement of product safety, sensory qualities, technological stability, sufficiently high efficiency of manufacturing processes, economic use of the available resources, and repeatability of the production cycle. As a result, even a purely technological issue that seems to have nothing to do with management how to make frozen baked products softer after storage -may be related to many other factors including functionality of the raw materials, moisture balance, condition of yeast used in the dough, mixing, proofing stage completion, quick freeze, stability of the storage temperature, and subsequent proper defrosting. That is why it is important to develop a system of justifications that considers all the above-mentioned aspects and allows for achieving a comprehensive result. It is precisely at this point that integrated justification systems begin showing their value [16, 21, 23, 24].

However, there is another reason why traditional mathematical or analytical approaches may prove ineffective in optimizing food production processes. To make decisions, companies typically rely on some information - recipes, laboratory results, data on process parameters and quality, and so forth. However, there is much more data that is not structured - technologists' experience, work instructions, SOP documentation, results of auditing, actions taken to correct problems, analysis of complaints received, suppliers' specifications, or reasons for changes in the manufacturing process.

This type of information makes it hard for traditional models and BI systems to work properly since it is necessary not only to process information and perform calculations but also interpret it, draw connections between different types of data, explain something, and justify decisions made. From this perspective, LLMs appear especially promising since their ability to combine knowledge in different forms proves invaluable for generating coherent justifications of solutions found [8, 21, 22, 30].

Nevertheless, in the case under consideration, the development of LLMs-based decision support systems implies certain restrictions as well. Namely, despite the rapid evolution of the technology in question, in no way can it be considered a reliable replacement for experienced specialists whose responsibility is very high. The analysis of the literature shows that in areas that require careful consideration, artificial intelligence should serve as a supporting tool for making decisions based on documented explanations, rather than as a source of unaccountable recommendations [3, 4, 8, 30].

2.1. Analysis of Relevant Researches and Digital Solutions for Improving Food Quality and Processes

When reviewing the body of similar research, it is immediately apparent that the application of artificial intelligence in the food industry is no longer a novelty in and of itself. The latest discourse no longer revolves around the question of whether AI can be useful at all, but rather around the levels at which it creates the greatest value and the conditions under which that value is actually realized. Aghababae and co-authors emphasize that in agri-food systems, AI today covers a very broad spectrum - from primary production, quality monitoring, and the supply chain to the analysis of final product characteristics, safety, waste reduction, and process optimization [16]. This indicates that artificial intelligence in the food sector has already moved beyond the narrow stage of experimental technology and is increasingly becoming part of the broader digital transformation.

However, an analysis of similar studies shows that the majority of published works in the food sector still focus on clearly defined technical tasks. One large group of studies is related to computer vision, hyperspectral analysis, or other methods designed to classify raw materials, detect defects, or predict certain quality indicators. Another group focuses on the integration of sensors, IoT, and machine learning for real-time monitoring. A third group examines process modelling, forecasting, and optimization, primarily based on structured data. The fourth group addresses broader changes in Industry 4.0, Quality 4.0, and Food Processing 4.0, where different technologies are viewed as components of a common architecture [17-21]. This classification is important because it helps to more accurately define this projects landscape as it is not merely a study of computer vision, not just work on recipe optimization, and not merely a theoretical overview of Industry 4.0. It attempts to integrate the levels of product, process, and solution interpretation into a single system.

The work on Food Quality 4.0 is fundamentally changing the way quality management is understood in the food industry. Hassoun and co-authors emphasize that traditional quality assessment methods are often too slow, destructive, labour-intensive, or insufficiently integrated into real-time production decisions, which is why increasing attention is being paid to digital and automated analytical tools [20]. The core idea of these works is that quality is increasingly becoming not just a final product inspection, but a continuous information and analytical system that integrates monitoring, data processing, and decision support. This approach is very important for your work, as it also does not treat quality as merely a result that we see after baking. It is treated as a dynamic state of the system, dependent on the interaction between the formula, the process, and external conditions.

The literature on Food Processing 4.0 extends this idea to the process level. Recent reviews show that the digitization of food production becomes most valuable when sensors, AI, big data, robotics, and process analytics are not implemented in isolation, but are integrated into a network of functional solutions [21]. This is important because many real-world food production problems do not arise from a lack of measurement. The problem is more often that the measured information remains fragmented, insufficiently linked, or underutilized in decision-making.

Therefore, the literature on Food Processing 4.0 essentially supports the logic of this work - the greatest value arises not where data is merely collected, but where it becomes the basis for clear, well-founded, and practically implementable recommendations [21, 22]. It is also very significant that systematic studies in recent years have moved beyond merely listing technological advantages to also analysing the constraints on implementation. Semercioz-Oduncuoglu and Luning have shown that the integration of Industry 4.0 technologies into food quality and safety control systems is hindered not only by technological barriers but also by managerial and organizational constraints - data fragmentation, lack of standardization, complex integration with existing systems, lack of expertise, and an economic return that is not always clear [22]. Such insight is very important the projected work because it means that simply “demonstrating the potential of AI” is not enough. It is needed to theoretically justify how a specific solution fits into the organizational reality. This is precisely why LLM is the tool used in this project not as a standalone technological demonstration, but as a potential bridge between knowledge, documents, process information, and decision-making.

Turning to LLM, the field of related research is even newer, but is already taking shape quite clearly. A systematic review by Ouerghemm and Ertz shows that the application of LLM in digital manufacturing is becoming particularly promising in areas where it is necessary not only to predict or classify, but also to structure information, improve human-machine interaction, interpret documents, assist in managing process knowledge, and explain the logic behind complex decisions [8]. This is a very important distinction. It allows to differentiate LLM from traditional machine learning models. A traditional model can help predict a certain outcome, but LLMs are theoretically interesting in that they can explain possible causes, combine multiple sources of information, and present several scenarios that a person understands not only as numbers but also as meaningful suggestions [8, 30].

Of course, the literature also clearly highlights the risks associated with such approach. Torkamaan and co-authors emphasize that the integration of large language models into socio-technical systems poses risks due to overreliance on conclusions that sound natural but are not always well-founded, as well as due to bias, the blurring of lines of responsibility, and errors that are difficult to detect [3]. This is particularly relevant to food production, where a recommendation can affect not only the sensory outcome but also safety, traceability, compliance with procedures, or economic losses. Consequently, the current scientific consensus is increasingly shifting toward the view that the value of LLMs in industrial systems is realized only when they operate within more strictly constrained, knowledge-enhanced, and human-controlled architectures [3, 4, 8, 30].

The principle of retrieval-augmented generation is particularly important here. Bitterman and co-authors demonstrate that RAG enables generative models to draw on an external, up-to-date knowledge base, thereby reducing the risk of hallucinations and increasing the reliability of responses [4]. Kishore and co-authors’ work on the use of citation-backed RAG for scientific literature synthesis further reinforces this trend where the model’s value increases most when it does not speak from general knowledge but relies on specific, cited sources and can provide a traceable answer [30]. Although these works examine the contexts of health or scientific literature synthesis, the principle can be applied quite directly to food production - instead of clinical guidelines or articles, SOPs, recipe versions, raw material specifications, a history of quality incidents, laboratory evaluation protocols, or process data archives can be used here [4, 8, 30].

The analysis of similar studies also has a product-level dimension. In recent years, the literature on frozen dough and frozen baked goods has seen a significant shift in focus from individual quality indicators to multi-faceted degradation mechanisms. In their review, Zhang and co-authors demonstrate that the quality of frozen dough deteriorates through several interrelated pathways that include yeast is damaged, the gluten network weakens, starch behaviour changes, water redistributes, and undesirable structural changes intensify during storage [23]. Aria and co-authors emphasize the role of cryoprotectants, while Zhu and co-authors specifically demonstrate that certain plant-derived cryoprotective components can significantly influence water status, gluten structure, and storage stability [24, 25]. These studies are important because they very clearly confirm one of the central tenets of this work - the quality of frozen baked goods is a systemic phenomenon, so it makes sense to manage it not with isolated tricks, but rather with a more integrated model of solutions.

A previously performed study adds a practical dimension to this general line of research. It has already been demonstrated in previous work that the sensory and structural properties of frozen baked goods can be specifically influenced by changes in the recipe, and that image analysis, combined with sensory evaluation, provides a meaningful basis for comparing results [9]. This is a very important theoretical and methodological bridge, as it allows this project to be based not on a completely new idea detached from context, but on a continuous line of reasoning, whereas previous research focused on how recipe changes affect quality, it is now reasonable to move on to the question of how to integrate such knowledge into a broader LLM-based DSS architecture.

To summarize the field of similar research, it can be stated that the focus of this work is based on at least four clearly established scientific trends as seen in Table 1. First, quality and process management in the food industry is increasingly moving toward the Quality 4.0 and Food Processing 4.0 models [17, 20, 21]. Second, AI in the food sector has already proven its value in tasks such as data interpretation, risk detection, classification, and optimization [16, 19, 22]. Third, LLMs in a production environment are promising when they act as a layer for information integration and interpretation, rather than as an autonomous decision-maker [3, 8, 30]. Fourth, the problem of frozen baked goods quality is sufficiently complex and multifaceted that this type of DSS is not only theoretically interesting but also practically justified [23-26].

Table 1. Related Areas of Research and Their Relevance to This Work

Research focus	The main focus in the literature	Practical significance for the food industry	The significance for this work
Food Quality 4.0	Digitization of quality control, automated data processing, integration of quality management	Enables a shift from final product inspection to continuous quality monitoring	Justifies the need for a QMS that integrates quality, process, and data
Food Processing 4.0	Process monitoring, digital models, real-time data analysis	Helps improve process stability and reduce losses	Justifies the inclusion of process parameters in the DSS
AI for food quality control	Defect detection, classification, prediction, and risk assessment	Increases accuracy and reduces reliance on manual evaluation	Demonstrates that AI already has practical value in the food sector
Integration of LLM into manufacturing	Interpretation of unstructured data, scenario generation, human-system interaction	Useful in contexts where decisions are based on documents, history, and expert knowledge	Directly supports the choice of LLM as the DSS layer
Tests on frozen dough and baked goods	Mechanisms of quality degradation, cryoprotection, storage stability	Enables more precise control over formulation and process decisions	Justifies the selection of frozen yeast-leavened baked goods as a model system

2.2. The Suitability of LLM-Based Decision-Making Systems for Food Production

To provide a theoretical basis for the application of LLM in food production, it is important to start with the nature of the decision-making environment itself. Food production decisions are almost always multifunctional. On the one hand, a technological outcome must be achieved: the right texture, volume, structure, moisture retention, or stability after storage. On the other hand, one must not exceed the limits of safety, hygiene, traceability, and company procedures. Thirdly, decisions must be economically sound and not have excessive raw material costs, high scrap rates, or also a complex production process window may be unacceptable, even if the product looks good in the laboratory. This multi-criteria logic means that the quality of decisions in food production is inseparable from the ability to integrate technological, quality, and management data [1, 2, 17, 22].

Traditional statistical and machine learning methods can be very useful in this environment, but they have a fairly clear limitation because they typically require data that is sufficiently structured, standardized, and clearly described. In the reality of food production, such order exists only partially. Laboratory indicators, recipe percentages, or temperature curves can be structured, but unstructured sources are no less important for decision-making, for example a technologist's notes, comments from raw material suppliers, audit findings, explanations of complaints, informal knowledge about "what usually works", the history of recipe changes, differences in work instructions between production lines, or even differing interpretations of the same phenomenon among quality, production, and R&D departments. Such situation clearly illustrates why LLM is theoretically interesting in this field because it can help semantically connect what classical analysis often fails to capture [8, 21, 22].

At this point, it is worth highlighting one important principle that in food production, an LLM should not be viewed as a better predictor than all other models, but rather as an intermediary between human and organizational information. In other words, it is not at its strongest when it comes to very precisely predicting a single, clear numerical result from well-defined variables. Its strength is better revealed when it is necessary to quickly gather context, compare information from multiple sources, explain possible causes, propose several alternatives, and show which documents or evidence they are based on [8, 30]. It is precisely this role that is particularly valuable in food production, as technological solutions are often interdisciplinary and rarely limited to laboratory data alone.

The need for semantic integration in the food industry is real and practical. The same problem can be described very differently across different departments. For example, a production worker might say that a product "didn't rise properly", a quality specialist might say it "doesn't meet volume specifications", and a technologist might say that "gas retention capacity has weakened due to a change in structure". These formulations describe the same phenomenon, but to a system that cannot handle semantics, they may appear as completely different problems. In theory, an LLM can help bridge this semantic fragmentation into a single meaningful decision space [8, 22].

The second key argument in favour of LLM suitability is interpretability. In a food production environment, a recommendation is often not useful if it is presented solely as the output of a black box. It is necessary to know why a particular correction is suggested, under what conditions it should work, what risks are associated with it, and whether it aligns with existing procedures and resource constraints. LLM, especially when operating on a RAG basis, can not only generate a scenario but also explain which documents, previous records, or known mechanisms the scenario is based on [4, 8, 30]. This capability is particularly valuable in the food industry, as it enables traceability and reduces the risk of unconsidered decisions. The third argument is the ability to generate scenarios. In food production, there is often no single, absolutely correct answer, more often, several realistic options are needed, which a person evaluates based on technological suitability, costs, risk, and feasibility. For example, a problem can be solved by changing the formula, changing the process, or combining both approaches. In such cases, the decision-making system must not only calculate but also present the alternatives in a structured manner. This is one of the areas where LLM is theoretically particularly well-suited, as it can generate not just a single answer, but several reasoned scenarios, each with its own logic and limitations [8, 30].

However, it would be a mistake to view the suitability of LLMs for food production as self-evident or unconditional. The analysis by Torkamaan and co-authors clearly shows that generative models in socio-technical systems can foster excessive trust, especially when their responses appear coherent and human-like, even though they are not sufficiently grounded in reality [3]. Such risks are particularly significant in food production. For example, even advice that sounds logically sound from a technological perspective may be inappropriate if it does not take into account allergen management, permissible raw material limits, equipment constraints, legislation, or a specific company's validated process window. For this reason, LLM cannot be implemented here as a standalone "chatbot". It must be restricted, linked to a relevant knowledge base, and operate within the human decision-making cycle [3, 4, 8].

In this context, retrieval-augmented generation is not merely an additional feature, but a central prerequisite. RAG allows the model's response to be reinforced with real, externally sourced data, thereby reducing the likelihood that the model will "make up" a technical explanation or overlook an important procedural boundary [4, 30]. In food production, this means that the LLM must rely not on abstract learning from general internet data, but on specific sources like recipe versions, SOPs, HACCP plans, raw material certificates, laboratory test histories, defect analyses, change documentation, and so on. Such an architecture theoretically allows for the reconciliation of two things that often seem difficult to reconcile - generative flexibility and procedural traceability [4, 8, 30].

The human role in this system also remains essential, the literature on the use of LLMs in high-stakes contexts increasingly shows that the greatest value is achieved not when the model is used autonomously, but when it operates within the human decision cycle as an interpretive and context-summarizing layer [3, 4]. In food production, this means that the technologist, quality specialist, or R&D employee remains the owner of the final decision. The system helps them not to decide for them, but rather to see connections, scenarios, and possible consequences. Such a division of roles is not only technically safer but also more plausible from an organizational standpoint, as responsibility for decisions in companies cannot, in any case, be transferred to a generative system.

Therefore, when evaluating the suitability of LLM for food production from a theoretical perspective, it can be argued that it is justified when four conditions are met. First, the problem must be sufficiently complex that numerical rules alone are insufficient. Second, the solution must require unstructured or documentary information. Third, the system must operate in a transparent and traceable manner. Fourth, the decision must remain under human control. So this shows that the case examined in this project aligns precisely with required logic and the choice of an LLM-based DSS is theoretically justified not only by its novelty but also by its functional suitability [3, 8, 22, 30].

2.3. Why Frozen Baked Goods are a Suitable System for Implementing such a DSS

The frozen baked goods system is particularly well-suited for the application of LLM-based DSS because quality is determined through a long chain of interrelated stages. Frozen baked products group immediately introduces several additional layers of complexity that simpler, freshly made products do not have - the dough must remain technologically viable after freezing, maintain sufficient structural stability during storage, and still achieve an acceptable sensory result after thawing and baking. In other words, the final product here depends not on a single moment, but on how the entire system navigates the transitions between several physical and biological states [23, 24].

Zhang and co-authors emphasize that the mechanisms of frozen dough degradation must be understood in a multifaceted manner - the state of starch, gluten, lipids, and yeast changes, the distribution of water shifts, and these changes are further amplified during storage and thawing [23]. It is very important to note that these phenomena are not isolated. For example, water redistribution can simultaneously affect the gluten network, yeast activity, and ice crystal dynamics. Such interdependence is particularly beneficial to a system of decision-making, as it requires viewing not an isolated symptom, but the entire cause-and-effect network.

One of the most important factors affecting the crispness of frozen baked goods is the condition of the yeast. The work by Guo and colleagues shows that yeast in dough is more sensitive to freezing than yeast in suspension, and that damage to it affects doughs rheology, gluten conformation, protein depolymerization, and the state of water [28]. This is a very important point for this work, as it shows that even a seemingly microbiological issue in this system has direct structural consequences. In other words, if the system is to help solve a quality problem, it must be able to consider not only the recipe or the baking process, but also how biological components react to the freezing cycle [23, 28].

Another key issue is the formation and recrystallization of ice crystals. In their review, Zhang and co-authors emphasize that mechanical damage in frozen dough occurs primarily during freezing, storage, and thawing, when initially formed crystals grow over time and further damage the structure [23]. This is particularly relevant in the industry, as temperature fluctuations cannot always be avoided in real-world supply or storage cycles. So, these circumstances explains why the challenge of frozen baked goods quality cannot be reduced to the question of “which ingredient to add”, but more it is more like that the problem is essentially process-related and time-dependent - it arises throughout the entire cold chain [23, 24].

The article “The Effect of Terminal Freezing and Thawing on the Quality of Frozen Dough: From the View of Water, Starch, and Protein Properties” further reinforces this logic by demonstrating that temperature fluctuations in the terminal cold chain can impair dough texture, reduce elasticity, and promote undesirable structural changes [27]. This aspect is important not only as an additional mechanistic explanation. It also reveals that the issue of frozen baked goods quality has a managerial dimension in which quality stability depends not only on R&D solutions but also on how the entire production and storage cycle is controlled. This is yet another reason why the decision-making system must be sufficiently broad and not limited to the recipe level [21, 23, 27]. Another important argument in favour of frozen baked goods is that this is a product group of great industrial relevance. The logic of frozen semi-finished products allows companies to better plan production loads, separate production from the final preparation site, manage distribution more flexibly, and shorten final preparation time. However, these advantages of logistical flexibility also create additional quality vulnerabilities because the more stages between the formed dough and final consumption, the greater the potential for structural and sensory losses [23, 24]. This is precisely why this product group is a particularly good example of why decision-making systems capable of integrating recipe, process, and quality information are necessary.

A previous study performed by R. Ž. Palionis about frozen baked goods quality improvement using LLM is also highly relevant here. That study has already demonstrated that changes in the recipe for frozen baked goods are reflected not only in sensory evaluations but also in observable changes in crumb structure [9]. This practically reinforces the theoretical assumption that this system is sensitive enough to meaningfully generate and test the scenarios proposed by DSS. In other words, frozen baked goods are not only a theoretically complex system but also an empirically responsive one, changes in formulation and process are quite clearly reflected in the results [9, 23, 24]. There is another important aspect about the quality of frozen baked goods that they are often evaluated not only by an absolute threshold of goodness but also by how closely it resembles the experience of a freshly prepared product. This means that the goal here is not merely to create a technically edible product, but to create one that, after freezing and storage, still retains as much of the desired sensory profile as possible. Such a task inherently requires a delicate compromise between stability and acceptability. It is precisely in such tasks that a decision support system can be particularly valuable, as it allows not only for the detection of defects but also for thinking in terms of scenario logic on how to improve one property without compromising others [23-25].

Therefore, the choice of frozen baked goods for study is theoretically sound because it is a complex, multifaceted, process-sensitive, and industrially relevant system in which quality depends on the formulation, biological components, water status, freezing history, and subsequent processing as highlighted in Table 2. Such a system aligns very well with the logic of LLM-based DSS, as it requires integrating heterogeneous layers of knowledge and generating not a single correct answer, but rather contextual, interpretable, and practically verifiable scenarios [8], [23-28].

Table 2. The Main Mechanisms of Quality Degradation in Frozen Baked Goods and Their Consequences

Mechanism	**Technical essence**	**Potential impact on the product**	**Solutions associated with DSS in the environment**
Decrease in yeast viability	Yeast is susceptible to damage during freezing and storage	Poorer rising, lower volume, denser texture	Formula adjustments, review of rising and freezing protocols
Weakening of the gluten network	Mechanical and thermal stress reduces structural integrity	Reduced gas retention, uneven porosity, collapse	Adjustment of flour, emulsifier, hydration, and mixing parameters
Water migration	Redistribution of free and bound water	Feeling of dryness, structural instability, increased hardness	Selection of humectants, syrups, and cryoprotectants
Recrystallization of ice crystals	Crystals grow during storage, especially when temperatures fluctuate	Mechanical damage to the structure, poorer texture	Optimization of freezing, storage, and cryoprotective systems
Starch retrogradation	Structural changes occur during storage	Hardening, reduced softness, poorer sensory acceptability	Adjustment of enzymes, moisture balance, and formulation

2.4. Theoretical Basis for Formula-Level Decisions

2.4.1. A Formula as a Functional System

On of the most important aspect of this research is understanding that the recipe is not only a compilation of ingredients. In food technology, formulation represents a functional system where each ingredient has not only the role within itself but also with other ingredients that are in the mixture and the process itself. This is particularly noticeable for frozen baked goods whose performance properties depend a lot on water absorption, ice crystal formation, gluten stabilization, fermentation, starches, and sensory perception [23, 24].

Therefore, it would be impossible to make a theoretically justified choice based on which ingredient to use but rather what role the particular ingredient plays within the system as a whole. Similarly, when implementing LLM-DSS, it would not be possible to choose recipes based on the ingredient's name and it's amount. Instead, if LLM recognized that one ingredient affected water movement, another was responsible for system stability, another for fermentation activities and the latter for product sensory perception, a set of recommendations could be provided on a theoretically justified basis. In short, theoretical support of such a formula will inevitably lead to the semantic formulation of a recipe [8, 23, 24].

2.4.2. Water Management as a Central Issue in the Formula

There are many topics discussed in literature resources about the quality of frozen dough. For example, one can talk about water's role in the production and preservation of frozen dough. It is obvious that such repetition results from the following facts. Water plays an important role in this process serving as a carrier and a component having impact on structure, freezing process and sensory quality of the products made. Thus, in their article, "Deterioration mechanisms and quality improvement methods in frozen dough: An updated review", Zhang and co-authors prove that when frozen dough degradation occurs mechanical forces effect can be seen due to freezing and recrystallization of water. Changes in water mobility directly relate to quality deterioration [22].

A similar point is highlighted in the article "Cryoprotectants for Frozen Dough: A Review" by Aria and co-authors. In particular, authors mention that using cryoprotectants can be used primarily as means of protecting products against low temperatures, yeast cells destruction and maintaining product structure [23]. Therefore, one of the most important solutions at the formulation stage cannot be viewed simply as a measure of improving the quality of products but rather as a means of managing water state. In order to manage water state different humectants, sugar systems, certain hydrocolloids and other substances able to decrease free water volume are needed [23-25].

2.4.3. The Role of Sugars, Syrups and Cryoprotective Agents

Using sugar or syrup systems to sweeten or change the colour of the product is only a little portion of their potential influence on the final product. Sugar/syrups can affect the water activity, glass transition, ice crystals formation and final moisture softness. For this reason, the latest researches often consider such substances not only as flavouring ingredients, but as structural and cryoprotectant elements [24, 25]. It is very important since it enables us to formulate certain decisions according to functionality criteria and not according to standard definitions like "sweetener", "fat" and "enhancer". A paper written by Zhu and co-authors "Chickpea peptide as a plant-based cryoprotectant in frozen dough: Insight into the water states, gluten structures, and storage stabilities" shows how the usage of chickpea peptides as a plant-based cryoprotector can work when it comes to water states, gluten structure and dough storage stability at freezing conditions [24]. Although such ingredient suggested by the authors will hardly be included into the final formula of a new product, such approach used in this research is rather important since it supports the concept that an LLM-based DSS should consider the most appropriate mechanism of its management [23-25].

As already mentioned, one of the recent studies on such materials usage in dough proves the importance of such an approach in the sense that some modifications within sugar/syrup system resulted to be more efficient in comparison with fats addition [9]. Undoubtedly, this cannot be considered as evidence for using sugar/syrup components in preference to other ingredients. Nevertheless, it still proves that water and cryoprotection mechanisms might be the most important criteria for decision-making [9, 23, 24].

2.4.4. The Fat System, Emulsifiers and the Logic of Textural Stability

Fat remains an effective component for baked goods subjected to freezing, but the use of fat is aimed not at replacing carbohydrates serving as cryoprotectants or humectants but instead at improving the softness of the product, improving dough plasticity and providing a perception of smoothness. At the same time, according to the review of the literature and practical data, lipids do not represent a good option to counteract quality deterioration caused by freezing and in case the problem appears because of damage to yeast cells, water transfer, or mechanical action of ice crystals, lipids cannot be the solution, meaning that in theory, the presence of fat in conjunction with other constituents of the dough structure might be more appropriate [9, 23].

The fact that such emulsifiers and other components influence the interfaces, and their aim is to stabilize phases and gas cells makes it quite understandable that such substances would be more efficient than lipids themselves. As a result, taking into consideration these theoretical reasons, it is possible to claim that it is better to develop LLMs for DSS that include certain combinations of components rather than substitutes for one element [9, 23, 24].

2.4.5. Enzymes, Retrogradation and Texture Retention

Another important group of solutions, concerning enzymatic technologies and other anti-staling methods, should be mentioned. For frozen goods such as frozen bakery products, the issue of texture softness and consumer satisfaction will not be associated with the damage done to the dough only. The starch retrogradation in further steps should also be considered. That is why an enzyme can be applied to such a technological issue [23, 24]. It is once again very important to remember that the impact of this technology will be influenced by the other elements involved, including moisture content, composition of other ingredients and so on - it will have a systemic nature.

Thus, the right approach for this project is not based on belief in the magic solution that solves all problems, but on applying this particular solution into a system model. The required DSS, in order to operate effectively, will not only provide the formula of the ingredient that is to be used for achieving certain effect, but it will also determine what exactly should be done in order to tackle the problem, whether the matter of concern is low volume of the goods, hardening of textures or changes in porosity or anything else [23, 24].

2.5. Theoretical Basis for Process-Level Decisions

In the process of formulation, the main issue should be related to the interaction between ingredients. In relation to the process part, it is crucial to highlight the application of the recipe along the process chain. Regarding the topic of frozen baked goods, the quality of frozen bakery products depends not only on the choice of ingredients used in the recipe but also on the proper performance of operations like mixing energy, dough temperature, fermentation, the speed of freezing, storage and defrosting of the product. Therefore, it is clear that it becomes reasonable to discuss this issue within the context of the process as the recipe alone does not provide enough proof to substantiate the problem under consideration. Therefore, it becomes important to understand that the process is equally important to ensure high-quality output [21, 23, 27].

The process of mixing, during which gluten network is formed, is particularly important as it influences both the incorporation of air in the dough and its structural formation for further freezing in the process of production. The incorrect performance of mixing leads to such dough that looks appropriate on the surface but cannot withstand freezing and storing due to hidden defects. This aspect is very important not only from a technological perspective but also from the perspective of decision making, as a quality issue might emerge at an early stage of processing before being noticeable in the end-product. Thus, a good decision support system should not only identify a problem within the final product but also be capable of analysing the whole process [21, 23]. Another crucial step is related to incomplete dough proofing before freezing, which negatively influences the development of the product into appropriate size and creates additional weaknesses in the dough's structure that lead to shrinkage of the product and loss of gases. This is discussed in the article by Zhang and co-authors called "Deterioration mechanisms and quality improvement methods in frozen dough: An updated review" where it is stated that poor quality of the dough during freezing and thawing processes is dependent not only on freezing but also on preceding steps [22].

The processes of freezing and storing become very important because this is where ice crystals formation and transformation take place, redistribution of water, damage from mechanical action, and most importantly, from structural degradation [23, 24]. If any problems emerge either regarding the freezing process itself or temperatures during storing, it is almost certain that additional damage will occur in the system [23, 27]. It is very important to note, since this fact proves that achieving high-quality of frozen food cannot be restricted only to its formulation alone. The main point here is to understand how it would behave once implemented in the respective process window that is invalidated by an inappropriate cold chain [23, 27].

As per "The Effect of Terminal Freezing and Thawing on the Quality of Frozen Dough: From the View of Water, Starch, and Protein Properties" by Liu X and co-authors [26], fluctuations during terminal freezing and thawing cause deterioration of texture properties and elasticity properties along with changes in water, protein and starch properties [26]. Such fact becomes particularly important for the industry since the quality can deteriorate even if the formulation applied initially was close to perfection [21, 22, 26]. That is why, in this particular case, DSS will have to generate not only recommendations regarding the formula but should also consider how its implementation might work in terms of the entire scenario [21, 22, 26].

It should also be noted that defrosting technique chosen cannot be regarded as neutral since recent researches have proven that different techniques used for this purpose impact gluten network, texture and specific volume [26]. Although, in this specific work it is not necessary to analyse different defrosting techniques since the idea behind mentioning this problem is proving that it is not sufficient to take into account only formula while analysing processes of manufacturing of high-quality products [22, 26]. Similar views have been expressed by scholars in relation to Food Processing 4.0 and digital twins as well. Thus, according to Purlis, using digital twins in food processing becomes particularly useful in the cases where data of the process chain could be linked to the quality since it helps to better understand processes [18]. However, in this case, the reason why this literature review is presented is not that the to implement the digital twin solution to the problem, but it highlights the idea that quality management is not only associated with formulas but also with processes, which in turn can be represented in the form of causality network [18, 21]. All the above-mentioned facts lead to the conclusion about the necessity to include process perspective in the analysis of the work since it is crucial to improve quality in order to achieve positive outcomes [8, 18, 21, 23, 27].

2.6. Theoretical Basis of Quality Indicators

In order to build a decision-support system, it should be based on quality indicators that have meaning and applicability. In this regard, there is an opportunity to theoretically categorize quality indicators for this purpose into three layers: sensory, structural and physical and productive efficiency. This categorization is not formal but allows the harmonization of consumer level, inner state of the product, and the level of organizational value. Sensory indicators are critical because at some point the product will still be estimated not by the technology of its manufacturing but by how a person feels about it. With the help of ISO 13299, it is possible to estimate a sensory profile of the product in such a way that allows going further and evaluating certain features in a systematic manner [10]. In the case of frozen baked goods, softness, moisture perception, acceptable texture, high-quality aroma, and sensory harmonization are particularly critical. They are critical because first, they are linked to the experience of the consumer, second, they indicate how formula and production interact [10, 23, 24].

However, sensory assessment is not enough for us to be able to compare two scenarios. For this reason, structural and physical indicators are required. Particle porosity, pore size distribution, structural homogeneity, moisture retention capacity, and texture parameters are important because they allow to establish the link between changes in formula and process on one side and the result - on another. In other words, structural and physical indicators establish a connection between inner processes of the system and human perception of those changes. This connection is useful not only from the analytical view but also for building DSS since it allows evaluating different scenarios in depth [9, 29].

Recently conducted studies show that such logic is quite right. The article "Digital image analysis to assess the texture of bread products" claims that digital texture analysis can be fast, non-destructive, cost-efficient, and applicable to monitoring quality and process stability. Digital texture fingerprints obtained from such analysis can serve as benchmarks of production quality [29]. It is very important for this work because an ImageJ-based analysis of crumb structure was used in another previous study performed on similar products [9]. This fact suggests that such an approach is credible and feasible due to aligned logic of this approach in international literature, feasibility shown by previous work, and necessity to use objective quality indicators for DSS [9, 29].

Notably, the use of image analysis does not matter from the standpoint of its technical advancement but because of the fact that such analysis helps go from general observations to quantitative interpretation of structures. In other words, with the help of image analysis, it becomes possible to understand if crumb structure looks softer because of pore size, their distribution pattern, etc. It is important for DSS because it allows linking the differences in the quality indicators to certain structural features [9, 29].

The third tier of quality indicators consists of those reflecting manufacturing efficiency and management. It is important to mention because quality should not be perceived as an abstract term in food production. That means that any solution, which may improve the quality of the product, needs to prove its effectiveness in terms of production and costs - in case there is a high probability of defects, problems with production management, waste generation or increase of costs due to some solutions, then the application of such solution in an actual company will have no sense at all. That is why the relationship between quality and efficiency, repeatability, management, etc. is critical and Quality 4.0 literature supports that point of view [1, 2, 17, 22]. According to Hassoun and co-authors, digital quality analysis will reach its peak in performance when the solution will help not only to increase the efficiency of measurements but also the efficiency of management in general [20]. Simply put, it means that indicators should help to make a decision, not just provide information about the product. This approach fits perfectly well into this project since the LLM-based DSS in this case will not only analyse the differences in quality but also create scenarios of different solutions [8, 20, 21].

This is the main reason why, in this research, quality indicators will be viewed as a three-tiered structure. Consumer experience reflects sensory indicators, structure and physical indicators reflect processes going on inside of the product. Manufacturing efficiency reflects real value in terms of industry application. All in all, such concept not only provides theoretical justification for the research variables but also establishes an important connection between this and the methodology section of this project [9, 10, 20, 29].

2.7. The Theoretical Basis of LLM, RAG and the Human Role in Decision Architecture

As far as this research is dedicated to DSS architecture integrating LLMs, its theoretical justification is even more necessary than in the case of the application of it. Why was a LLM-based decision layer chosen but not some separate machine learning method? As far as the answer cannot be found only through technological considerations, it should rather be reached through functional necessities of the system [8, 30]. To begin with, the use of LLM is particularly convenient for such tasks where a problem needs to be formulated, sources need to be integrated, possible ways should be suggested and decisions need to be explained in natural language [8, 30].

Nevertheless, generativity alone is not enough to make a model useful for decision-making. According to Han and co-authors, while LLMs have such advantages as scalability, flexible use and adaptation to different contexts, at the same time, the very generality of these models might lead them to make false or insufficiently supported decisions [6]. For example, in food production, decisions related to technology should be based not only on a reasonable explanation but also on the possibility of tracking them back through documents. For this reason, RAG in this research is not just an optional addition to LLM, but a requirement. Bitterman and co-authors state that the purpose of the retrieval-augmented generation model is exactly in the opportunity of creating more reliable content with the help of extracting knowledge from outside [4]. Such notion finds additional confirmation in the works by Kishore and co-authors, according to which citations can serve as a guarantee for higher value of the information provided by the model [30]. In terms of food production, the role of citations is particularly important as decisions cannot be grounded only on the knowledge of the model, but also on the history of the recipe, documentation, procedures, and records [4, 8, 30].

Another essential characteristic of the suggested architecture is related to its socio-technological nature. According to the existing literature, the integration of LLM without specifying human involvement might be dangerous, as it leads to a risk of over-reliance, the inability to discover potential errors, and diffusion of responsibility [3]. In the context of food production, the involvement of a human into decision-making is especially crucial. While the proposed system can help explore potential scenarios, identify possible reasons for problems and provide a list of relevant documents and historical fragments, at the same time, the ultimate decision about the actions needs to be taken by the corresponding expert who possesses knowledge of the situation and the company [3, 4, 8]. Thus, the suggested architectural solution is quite relevant from a socio-technological point of view. The problem of companies in food production often lies in the lack of not the information, but the time to properly analyse it. At the same e time, technologists and quality experts in the field usually operate within several layers of information including lab results, recipes, supplier documents, incidents, customer information, and standard operating procedures. Therefore, the proposed architecture seems quite valuable in terms of food production [8, 22, 30].

2.8. Research Logic, Purpose and General Methodological Approach

The purpose of the second chapter of this work is to theoretically ground and methodologically design a research process that would allow not only for a conceptual description of the LLM -assisted digital decision support system, but also to test its suitability under real-world conditions for the tasks of developing frozen baked goods and managing the production process. Therefore, in this work, methodology is understood not merely as a sequence of statistical or laboratory procedures, but as a coherent model of design, data collection, scenario generation, experimental validation, and interpretation of results. This approach is based on the fact that in the food industry, quality is a multi-criteria category that depends on the interaction between the recipe, the process, and storage conditions, and the role of LLM in decision support is revealed only when this interaction is transformed into a clear structure of data and knowledge [6], [13], [14]. An overview of digital manufacturing shows that the value of LLM integration arises precisely where the model is incorporated into the actual flow of information and actions, rather than being used as an isolated text-generation tool [6].

From a methodological perspective, this work combines four complementary approaches: theoretical analysis, system design, experimental testing, and analytical evaluation of results. Theoretical analysis has already shown that LLM must be integrated into a robust socio-technical architecture based on RAG, human involvement, and traceability [3, 4, 6]. In this chapter, this logic is translated into the research design where first, quality-critical formulation and process variables in frozen baked goods are defined then second, a data and knowledge structure necessary for LLM-assisted scenario generation is created, third, an experimental validation is planned, based on the same fundamental methods already applied in a previously performed research project - controlled recipe variations, uniform production conditions, sensory analysis, and visual analysis of crumb structure [9]. In the previous project, a uniform technological regime was applied to all variants that included mixing, dividing, shaping, proofing to target volume, blast freezing, 4-month storage at -18 °C, 60-minute thawing, and baking under the same conditions, with results evaluated visually, via ImageJ analysis, and on a 9-point hedonic scale by an internal panel of 7 technologists [9].

It is precisely such continuity that constitutes one of the most important elements of the methodological foundation. The practical part of this project is not intended to discredit the logic of the previous research project, but rather to expand it into a higher-level system in which AI/LLM is used not only for recipe adjustment but also for managing the interaction between the recipe and the process. The previous report already raised the idea that the quality of frozen baked goods depends not only on the formulation but also on parameters such as dough temperature after mixing, the end point of proofing before freezing, the freezing curve, freezer load, and thawing duration; therefore, in this study, formulation and process control must be examined together [9]. Such methodology aligns well with the latest literature on frozen dough quality, which indicates that quality degradation occurs throughout the entire freezing process - during the freezing, storage, and thawing stages and that improving it requires coordinated actions at both the material and technological levels [17, 18, 19].

2.8.1. Research Subject, System Boundaries and Selection of the Product Under Study

The subject of this study is an LLM-assisted digital decision support system applied to improve the quality of a specific frozen yeast-based baked good. A viable product model must be selected so that it is sensitive enough to changes in the recipe and process, while also being realistic enough for an industrial environment. For this reason, the most suitable object is a frozen yeast-raised baked good, whose final quality after storage and baking heavily depends on gas retention capacity, crumb structure stability, moisture retention and sensory acceptability. This choice is based on several arguments.

First, frozen yeast-raised baked goods are a technologically sensitive product group, as they are simultaneously affected by a decline in yeast viability, weakening of the gluten network, water migration, and the impact of ice crystals [20, 21, 23, 24, 28]. Second, a previously performed project by on yeast-raised frozen products has shown that even minor changes in the recipe of this type of product can result in clear enough differences in both sensory characteristics and crumb structure [9]. Third, in this product group, it is possible to quite clearly separate between the effects of the formula and the process if the experimental conditions are controlled consistently.

The scope of the system must be clearly defined in this work. First of all, the DSS should not be designed for the entire factory or all the products, it should be designed for a single product class and a specific quality issue. Such limitation is methodologically logical, because it ensures sufficient depth and avoids a superficial model for all products. Secondly, the DSS output in this work is not considered a final, automated directive, it is a limited set of scenarios that is reviewed and approved by a human. Third, not all possible operational KPIs will be modelled simultaneously during the study, priority is given to those indicators that are directly related to product quality and can be logically linked to resource efficiency, such as defect risk, stability, uniformity, and the potential reduction of unnecessary testing [3, 17, 22].

2.8.2. Principles and Architecture of LLM-Assisted DSS Design

The system being designed should be understood as a multi-layered decision making environment that integrates knowledge about the recipe, the process, quality indicators, and the company's practical constraints. The main principle is that the LLM is used in this work as a component for explaining decisions and generating scenarios, but not as a standalone optimizer. This logic is directly linked with the current literature on LLM integration into digital manufacturing and socio-technical systems, which emphasizes that the model's value is best realized where it operates in conjunction with other layers of information, RAG, and human-in-the-loop principles [3, 4, 8, 30].

Methodologically, the architecture of this system can be divided into four layers as showcased in Table 3. The first layer consists of a knowledge base. It must contain information about potential raw materials, their functional properties, dosage limits, possible substitutes, labelling or allergen restrictions, as well as previous tests, literature guidelines, and product technical instructions. The second layer consists of structured product data like the current formula, process parameters, reference quality indicators, and the identified problem. The third layer is made of the RAG + LLM module, which generates scenarios based on this information. The fourth layer is made of a human evaluation and selection part, in which a researcher or technologist decides which scenarios are sufficiently justified for experimental verification.

It is very important to make clear in advance what type of output is considered a valid decision unit in this project. It is proposed that the LLM does not return a single generalized recommendation, but instead generates 2-4 structured scenarios. Each scenario must be described using the same logic - a proposed change to the formula, a proposed change to the process, the expected impact on selected quality indicators, a mechanistic explanation, and potential risks and limitations. Such format allows a person to compare alternatives and reduces the risk that the AI's output will be interpreted as an definite truth.

Table 3. Layers of an LLM-Assisted Digital Decision Support System

System layer	Content	Purpose	Expected result
Knowledge Base	Raw material specifications, technical instructions, previous tests, regulatory guidelines	Ensure domain context	The model is based on current and limited information
Structured product data	Existing formula, process parameters, quality indicators, identified problem	Define the specific product context	The model receives a specific task rather than a general one
RAG + LLM Module	Query analysis, relevant information retrieval, scenario generation	Generate well-founded solution options	2–4 structured scenarios with explanations
Human Evaluation Module	Expert review by a technologist or researcher	Select realistic solutions	Only technically feasible scenarios are included in the experiment
Experimental Feedback Module	Sensory, structural, and other outcome data	Verify the benefits of DSS and generate new knowledge	Confirm or reject scenarios

Since the literature clearly shows that RAG reduces the risk of hallucinations in generative models and helps maintain contextual accuracy, such methodology must ensure that the model operates only with relevant, contextual data [4, 30]. This means that the model should not be "fed" with random, unstructured documents. Standardized product input will give better output quality, where all information is presented using the same template: product type, problem, current formula, available raw materials, process constraints, target quality metrics, and undesirable trade-offs.

2.8.3. Selection of Quality-Critical Formulation and Process Variables

In order for the created system to generate technologically logical and viable scenarios, it is important to identify which recipe and process variables are critical for the selected product. Reviews of frozen dough quality deterioration show that the key degradation mechanisms are related to the state of water, ice crystal formation, damage to the gluten network, decreased yeast viability, and ingredient migration [20, 21, 23, 24, 28]. It shows that, at the formulation level, the most critical variables are those that can impact at least one of these mechanisms. In this work, such variables should include the type and amount of sugar, the use of syrups, the type and amount of fat, the dough hydration level, the inclusion of components with cryoprotective effects, the use of emulsifiers, and, if relevant, variations in flour properties between batches. A previous study has shown that a partial replacement of sucrose with glucose syrup improved porosity and sensory acceptability, therefore, it is methodologically sound to consider such mechanisms as important starting points for LLM scenario generation [9].

To make sure such variables are useful to the DSS, it is recommended to create an attribute table for each one. It should include the following fields: variable name, technological function, expected impact on quality indicators, interaction with the process, constraints, and possible substitutes. Such format allows the model to be equipped not only with ingredient names but also with their functional logic. This is particularly important because the LLM must not only see the list of raw materials but also understand what mechanism a specific raw material can be useful for controlling [8, 16, 24]. Process variables in this study should be considered equivalent to formula variables.

Based on a previous study and recent literature on frozen dough, the most important process variables are dough temperature after mixing, mixing duration and intensity, the end point of proofing before freezing, freezing rate, freezer load, storage duration and temperature stability, and thawing time and conditions prior to baking [9, 20, 21, 23]. If the DSS is to generate truly useful solutions, it must take into account that the same formula can yield different results depending on how this technological chain is managed.

Table 4. Quality-Critical Formulation Variables for the DSS System of Frozen Baked Goods

Variable	Technological function	Likely impact on quality	Possible constraints
Type and amount of sugar	Control of sweetness, water activity, and mobility	Can affect softness, perceived moisture, and ice crystal behaviour	Price, labelling, flavour profile
Syrups / humectants	Water-binding, cryoprotective effects	May improve structural stability and reduce dryness	Formulation balance, viscosity, cost
Type and amount of fat	Mouthfeel, tenderness, dough workability	May improve tenderness, but does not always prevent structural degradation	Cost, changes in texture, labelling
Emulsifiers	Stabilization of phase interactions, maintenance of gas cells	May improve porosity and structural integrity	Acceptability, consumer expectations
Hydration level	Dough rheology, gluten development, water state	Directly affects structure, porosity, and softness	Process sensitivity
Cryoprotective ingredients	Protection against freeze-thaw cycles	May reduce quality loss during storage	Availability, dosage limits

It makes sense to divide the process variables into four groups of pre-freezing, freezing, storage, and post-freezing. Such grouping is useful because it allows not only for data collection but also for a more precise interpretation of where the scenario should be applied. For example, if the problem involves volume loss after baking, one group of scenarios could focus on the pre-freezing stage, another on cold cycle management and a third on a combined adjustment of the formula and the process.

Table 5. Quality-Critical Process Variables for Evaluating the Quality of Frozen Baked Goods

Process stage	**Variable**	**Potential impact on quality**	**Risk of deviation from the optimal range**
Mixing	Mixing time and intensity	Gluten network development, incorporation of air	Structure that is too weak or overly damaged
Mixing	Dough temperature after mixing	Yeast activity, dough stability	System too active or unstable before chilling
Proofing	End point of proofing	Volume potential and structural strength	Settling or insufficient volume
Freezing	Freezing rate	Ice crystal size and its effect on structure	Larger crystals and greater damage
Storage	Temperature stability	Degree of recrystallization	Deterioration of structure and increased hardness
Thawing	Thawing duration and conditions	Final structural recovery before baking	Collapse, uneven porosity
Baking	Baking mode	Final texture, volume, colour	Under or over baking

2.8.4. Data Collection Strategy and LLM Query Methodology

For the DSS to function effectively, it is important to establish a clear data base. It is recommended to divide the data into four blocks like recipe data, process data, quality data, and performance/efficiency data. The recipe block should include a list of ingredients, their percentages, functional classes, possible substitutes, and, if possible, cost information. The process block should include all key production parameters. The quality block should include sensory scores, visual assessment, ImageJ metrics and additional baseline metrics such as volume or moisture. The performance block may include defect characteristics, stability notes, and other practical indicators that help link quality to resource efficiency [17, 20, 22]. Each test must be counted as a separate, clearly identifiable batch. This is necessary so that inputs and outputs can later be linked, for example which formula and which process parameters had specific sensory and structural results. This logic is also consistent with the Quality 4.0 approach, in which quality data must not only be collected, but also linked to the decision cycle [17, 20].

LLM prompts in this study must be at least partially standardized. It is proposed to use a five-part prompt structure: product description, current problem, available formulation and process data, constraints, and desired output format. For example, a query could be formulated so that the model receives information about a frozen yeast bun-type product, its current structural problem after 4 months of storage, a list of permitted raw materials, and technological constraints, and then be asked to generate three realistic scenarios with a brief rational explanation. Methodologically, it is very important that scenarios be generated not as free text but according to a standardized output format as shown in Table 6. It is recommended that each scenario includes the following sections - scenario title, proposed formula changes, proposed process changes, expected impact on quality indicators, rationale, and potential risks. This structure allows scenarios to be compared with one another, filtered later, and the entire DSS operation documented.

Table 6. Standardized Structure of an LLM-Generated Script

Script element	Content	Purpose
Script Title	Brief technical description of the script	Enables the identification and comparison of scripts
Proposed changes to the formula	What changes are proposed to the formulation	Shows the formulation intervention
Proposed process changes	Proposed changes to the process parameters	Shows process intervention
Likely mechanism	Why the scenario should work	Ensures clarity
Expected impact on quality	Which indicators should improve	Links the scenario to the evaluation criteria
Possible risks	What side effects may occur	Assists with expert selection
Recommended validation metrics	What needs to be verified experimentally	Guides the experimental work

2.8.5. Expert-Led Scenario Selection and Experimental Validation Plan

Not all scenarios generated by the LLM need to be incorporated into the experiment. Therefore, the methodology must include an expert filtering stage. In that stage, each scenario must be evaluated based on at least four criteria: scientific validity, technological feasibility, alignment with the company's constraints, and the likely impact on the specific problem. This step is very important because the literature on the use of LLMs in complex systems highlights that the human role must remain active not only at the final approval stage but also during the selection of solutions [3, 8, 30].

For experimental validation, it makes sense to select at least three groups - a baseline product version, an LLM-assisted formula scenario, and an LLM-assisted formula + process scenario. Such design is much better compared to a simple "baseline vs AI" comparison because it allows for an assessment of how much value is created by formula correction alone and how much additional benefit is gained from incorporating process adjustments. If the scope of work is limited, the number of scenarios can be reduced, but the methodologically strongest option still is a design with at least three comparable groups.

All scenarios must be produced using the same baseline method, the same equipment, and by maintaining non-experimental conditions as uniformly as possible. The logic of the previously performed study is very useful here it shows that uniform mixing, portioning, shaping, proofing, freezing, storage, thawing, and baking provide sufficient control so that differences in quality can be attributed more to the effect of the scenario rather than to random technological variation [9].

The time dimension of storage is also important in this study. Since the commercial value of frozen baked goods depends on their stability over time, it is recommended to evaluate more than one storage point. It would be optimal to use at least the 0, 2, 4, and 6-months points. If resources are limited, it can be chosen to use 0, 4, and 6 months, however, it is necessary to clearly justify why these specific points were selected. This strategy allows for the evaluation not only of the immediate quality effect but also of the trajectory of quality change, which is particularly important in the case of frozen products [20, 21, 23].

2.8.6. Sensory Analysis, Structural Analysis, Data Processing, Reliability and Ethics

Sensory analysis serves as an essential layer of validation in this study, as the ultimate goal of the product is not only technological stability but also a sensory experience that is acceptable to the consumer. Since a 9-point hedonic scale was already successfully used in a previous study about yeast-raised products with an internal panel of technologists, it is methodologically appropriate to maintain the same basic logic [9]. However, for this project, the procedure should be further standardized based on the principles of ISO 13299, ISO 6658, and ISO 8586 [10, 31, 32]. This entails a clearer definition of evaluation attributes, uniform sample coding, a uniform serving temperature, a randomized serving order, and a clearly described status of the evaluators. The primary sensory attributes should be considered to be overall acceptability, softness, moisture sensation, textural acceptability, and, if relevant to the product, aroma quality as shown in Table 7. This set is sufficiently clear and, at the same time, directly related to the most common problems with frozen baked goods. If possible, a separate group of technologists and a small group of untrained consumers can be formed, but if resources are limited, it is entirely acceptable to stick with a single, clearly defined group of evaluators.

Table 7. Hedonic Scale Used for Sensory Evaluation of the Produced Products Based on LLM Generated Suggestions

Hedonic scale	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Texture	Dislike extremely	Dislike very much	Dislike moderately	Dislike slightly	Neither like nor dislike	Like slightly	Like moderately	Like very much	Like extremely
Softness	Dislike extremely	Dislike very much	Dislike moderately	Dislike slightly	Neither like nor dislike	Like slightly	Like moderately	Like very much	Like extremely
Moisture	Dislike extremely	Dislike very much	Dislike moderately	Dislike slightly	Neither like nor dislike	Like slightly	Like moderately	Like very much	Like extremely
Aroma	Dislike extremely	Dislike very much	Dislike moderately	Dislike slightly	Neither like nor dislike	Like slightly	Like moderately	Like very much	Like extremely
Overall acceptability	Dislike extremely	Dislike very much	Dislike moderately	Dislike slightly	Neither like nor dislike	Like slightly	Like moderately	Like very much	Like extremely

For instrumental or semi-instrumental structural analysis in this study, it makes the most sense to use ImageJ-based soft tissue analysis. In a previous similar study, this method was already used to calculate the number of pores, average pore size, and total porosity [9]. Recent literature on digital analysis of bread texture indicates that this is a sufficiently sensitive and practical method suitable for monitoring quality and uniformity [29]. In project, it is important to expand such method by standardizing the conditions for image acquisition: uniform slice thickness, uniform lighting, the same resolution, the same thresholding method, and multiple slices for each batch. In this way, ImageJ becomes not merely an additional illustrative method, but a full-fledged layer of quality measurement.

Data analysis should focus on two tasks mainly - determining whether the scenarios proposed by the LLM improved the product, and assessing whether the DSS itself created value in the decision-making process. In the first case, it is recommended to use descriptive statistics, compare means and standard deviations, and, if the amount of data allows, apply simple statistical tests. However, the most important aspect of this work is not statistical complexity, but a clear connection between the problem, the scenario, and the result. If the scenario was theoretically intended to improve water management and gas retention, the analysis must show whether this was reflected in the structure and sensor scores. In the second case, the benefits of the DSS itself must be evaluated. It is proposed to record how many scenarios the model generated, how many were rejected, how many were selected for validation, how long it took to prepare the scenarios, whether they were technically meaningful, and whether they helped reduce the number of unnecessary tests. Such an analysis is important because this work evaluates not only the product but also the LLM as a decision-support tool.

Methodological reliability in this study is enhanced in several ways - a standardized product input scheme for the LLM model, a clearly defined selection of scenarios, uniform production conditions for all groups, blind coding of sensory samples, a uniform image analysis procedure, and clearly described evaluation criteria. It is also necessary to identify the study's limitations in advance. A single-product case study does not allow conclusions to be automatically generalized to all product groups. The quality of the LLM's output will depend heavily on the completeness of the knowledge base and the quality of the input. If a limited number of scenarios are validated, the results will be applicable rather than universally generalizable. However, in the context of this project, this is adequate, as the goal is not to create a universal platform, but to substantiate and test a specific DSS framework in the context of a real-world product. From an ethical standpoint, the study is low-risk but requires two things. First, proper participant informed consent and hygiene must be ensured during sensory evaluations. Second, if the company's formulas or technical data are used, the principle of commercial confidentiality must be maintained. LLM must be used as a recommendation tool, not as an autonomous decision-maker, and this must be clearly stated. This position is fully consistent with the logic of both food quality management and the responsible use of LLM [1-3], [8, 17].

2.9. Chapter Summary

The theoretical and methodological analysis in Chapter 2 demonstrates that the focus of this study is consistent from the perspectives of both food technology and digital solution systems. The theoretical section establishes that the quality of frozen baked goods is a complex, multi-criteria phenomenon dependent on the interaction of recipe, process, storage, and quality indicators [20-24], [27, 28]. It is also demonstrated that large language models in such an environment are meaningful not as autonomous decision-makers, but as human-supervised DSS components enhanced by RAG principles [3, 4, 8, 30]. The methodological section extends the following logic into a concrete research design. The study is based on the selection of a problem product, diagnosis of its current state, preparation of a structured knowledge base and data matrix, LLM-assisted scenario generation, expert selection, and experimental validation. Such sequence allows DSS to be evaluated not in the abstract, but at the level of real technological solutions. At the same time, it preserves a fundamental principle that LLM is used in this work as a tool for solution justification and scenario generation, but the final decision and its confirmation remains the responsibility of humans. Therefore, this chapter now serves as a perfect ground base between the theoretical justification of the problem and the practical implementation of the work. While the theoretical section demonstrates why an LLM-assisted DSS for improving the quality of frozen baked goods could be meaningful, the methodological section shows how a system can be designed, defined, tested, and evaluated in the context of a real product.

3. Project Solutions and Results: Application of an LLM-Based Decision-Making System to Improve the Quality Stability of Frozen Yeast-Raised Baked Goods

The main idea of this chapter is to present a practical application of the LLM-based digital decision support system model to a real frozen yeast-raised baked good. In chapter 2, it was established that the quality of frozen yeast-raised baked goods depends not on a single isolated factor, but on the interaction between the recipe, the technological process, the freezing regime, the storage duration, and the final preparation. Therefore, this chapter is meant to show that the LLM-based DSS is applied not as a standalone recipe generation tool, but as a structured method for decision search, scenario formulation, and experimental verification.

As the subject of this study it was chosen to take the frozen yeast-raised baked good “Lemon Curd Poppy Seed Loaf”, with a unit weight of 310 g. The product is made from yeast dough, a lemon curd filling and decorated with a ready to use liquid glaze and ground blue poppy seeds. The product’s manufacturing process follows the standard industrial logic for frozen yeast-raised baked goods as shown in Fig. 5., the dough is mixed, shaped on an automated line, filled, proofed, decorated, shock-freezing, stored frozen, and thawed only immediately before baking. The technical description of a similar product states that the dough is mixed in a spiral mixer for 5 minutes on low speed, 8 minutes on high speed, and another 2 minutes on high speed after adding the filling, with the target dough temperature after mixing being 20–24 °C. The proofing conditions in the analogous process are a temperature of 37°C, 70% relative humidity, and a proofing time of approximately 1 hour 10–15 minutes.

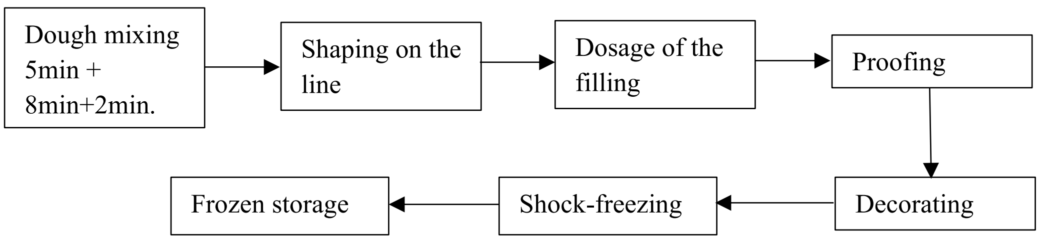

Fig. 5. Steps of Yeast-Raised Products Production

The practical problem is that the current product formulation and production process do not ensure sufficient quality stability throughout the 6 month shelf life of the frozen product. This problem is characteristic of frozen yeast-raised products, as long-term storage can lead to a decrease in yeast viability, weakening of the gluten network, water migration, recrystallization of ice crystals, and starch retrogradation. These mechanisms are identified in the latest literature on frozen dough as the primary causes of deterioration in product volume, porosity, softness, and sensory acceptability following storage and thawing [22, 23, 26, 27].

In an article “Deterioration mechanisms and quality improvement methods in frozen dough: An updated review” by Zhang and co-authors. it is emphasized that the degradation of frozen dough must be evaluated in a multifaceted manner, as the states of the yeast, gluten, starch, lipid, and water phases change simultaneously [22]. This directly aligns with the methodological approach of this study where the issue of product quality cannot be resolved simply by changing a single raw material or a single process parameter.

The purpose of this chapter is to demonstrate how the LLM-based DSS methodology developed in Chapter 2 was applied to a specific product, how the product data was structured, how alternative quality improvement scenarios were formulated, and how these scenarios were prepared for experimental validation. An analysis of the experimental results is presented later in this chapter.

3.1. Selection of the Product Under Study and Definition of Quality Issues

The product selected for this study, "Lemon Curd Poppy Seed Loaf", is an industrially produced frozen yeast-raised baked good with a unit weight of 310 g according to the current recipe. The product's structure is complex, the main part of the mass consists of yeast dough, the lemon curd filling provides additional textural and sensory effects, and the surface characteristics are formed using surface glaze and ground blue poppy seeds [32]. This product composition allows it to be considered a suitable model for testing a decision-making system based on LLM, as the product's quality depends on several interrelated factors that include the recipe, the process, the state of the water, fermentation, freezing, and final baking.

The choice of product is not random. Frozen yeast-based baked goods are one of those product groups where maintaining consistent quality over a long shelf life becomes a particularly challenging task. Unlike freshly baked goods, frozen yeast-based products must maintain their technological viability through several stages: dough preparation, shaping, proofing, freezing, storage at -18 °C, thawing, and baking. Quality degrading factors can arise at any of these stages. For example, even if the recipe is suitable for short-term storage, water migration, recrystallization of ice crystals, a decrease in yeast activity, or a weakening of the gluten network may become apparent within 6 months [22, 23, 26, 27].

The problem with the current product is defined as insufficient quality stability during a 6 months frozen storage period. Since the final experimental results are not yet presented in this section, the problem is defined as a technological hypothesis that must later be verified experimentally. The main hypothesis is as follows - the current recipe and existing process do not sufficiently stabilize the water status, fermentation potential, and dough structure throughout the entire 6 months frozen storage period, which may result in a deterioration of the final baked product's structure and sensory properties. The literature indicates that the loss of quality in frozen dough is determined by several interrelated mechanisms. First, long-term freezing and temperature fluctuations can cause the growth of ice crystals, which mechanically damage the dough structure [22, 26]. Second, yeast in frozen dough loses some of its viability, so gas formation, product volume, and porosity may decrease after thawing and baking [22, 27]. Third, the gluten network changes during freezing, which reduces gas retention capacity and increases the risk of structural collapse [22, 27]. Fourth, water migration between dough components, filling, and the ice phase can result in a dry mouthfeel, a harder texture, and uneven crumb [23, 26, 37]. This logic from the literature helps explain why the problem must be addressed not merely by increasing the amount of yeast or improvers, but by systematically managing the recipe and process.

The practical objective of this work is not only to propose a new framework, but also to verify whether an LLM-based DSS can help generate technologically sound, practically applicable, and experimentally verifiable decision scenarios. Therefore, the primary focus of analysis in this chapter is not merely the product, but the decision-making process itself. This logic directly aligns with the methodology outlined in Chapter 2 where LLM is used as a tool for generating and justifying scenarios, while the final decision must be experimentally verified and validated by a human.

To perform the evaluation of the LLM as a tool for generating and justifying scenarios it is needed to perform tests on the suggested solutions to address product quality issues, and in this study it is chosen not to search for a single “best” ingredient, but rather to compare two types of possible solutions with the already exiting formulation:

– the current control recipe and process;

– a scenario based solely on recipe changes;

– a scenario based on a combination of recipe and process changes.

Such chosen approach allows us not only to determine whether product quality can be improved, but also to assess which type of DSS proposal is more valuable in this scenario, a recipe adjustment alone or an integrated change to both the recipe and the technological process.

3.2. Original Product Formulation, Manufacturing Process, and Quality Risk Points

The original product recipe was structured according to the logic used in industrial bakeries, where ingredient quantities are expressed relative to 100 kg of flour. This method of calculation was chosen because it allows for an accurate comparison of the control and experimental scenarios, maintaining a clear relationship between recipe changes and the flour base. The control product recipe is presented in Table 8.

Table 8. Control Recipe for "Lemon Curd Poppy Seed Loaf" (K0), Based on 100 kg of Flour [32]

Raw material	**Amount, kg / 100 kg of flour**	**Functional purpose**
Flour C-550	100,000	Main structural phase of the dough
White sugar	15,220	Sweetness, fermentation substrate, regulation of water activity
Salt	1,740	Flavour, gluten strengthening, fermentation control
Wheat gluten	1,500	Strengthening of the gluten network
CO2MMITTED BRIOCHE FREE 5 % improver	4,960	Improvement of structure, fermentation, and softness in brioche-type doughs
Yeast	6,960	Gas formation, volume development
PRO-VOLMAX PF improver	4,000	Improvement of volume and structure
Rapeseed oil	18,000	Softness, plasticity, sensory characteristics
Lemon cream filling	40,847	Flavour, moisture and mass contribution
Ground blue poppy seeds	3,928	Surface decoration, sensory identity
Surface glaze	2,357	Surface finish
Water	44,000	Hydration, dough rheology
Total	**243,512**	

Based on the proportions per unit, this recipe yields a 310g product, consisting of approximately 250g of dough, about 52g of lemon cream filling, about 3g of surface glaze, and about 5g of ground blue poppy seeds [32]. These proportions are important because the amount of lemon filling and its water activity can affect the moisture balance of the dough, while the surface components can influence the final texture and sensory acceptability. The technological process was analysed based on the technical specifications of a very similar product a cinnamon yeast loaf. This analogue is suitable as a basis for the process because its production principle is essentially the same, the yeast dough is mixed in a spiral mixer, shaped on an automatic line, the filling is dispensed, the product is rolled, proofed, decorated, and chilled [33]. The main differences relate to the product's proportions and components: in the new product, a lemon cream filling is used instead of a cinnamon filling, its amount is increased to 52g instead of 50g, the dough weighs approximately 250 g, and ground blue poppy seeds are used on the surface instead of pearl sugar [32, 33].

The standard procedure specifies that the dough is mixed for 5 minutes on low speed, 8 minutes on high speed, then the scraps are added and the dough is mixed for another 2 minutes on high speed. The target dough temperature is 20-24°C [33]. This temperature range is important because yeast dough is sensitive to temperature changes - too high of a temperature can promote excessive fermentation activity before freezing, while too low of a temperature can result in insufficient dough development and a weaker structure. In the context of frozen yeast-raised baked goods, the dough temperature after mixing becomes one of the critical process variables, as it affects both yeast activity and the state of the gluten network prior to proofing and freezing [22, 27].

The products are formed on an automated line where the dough is calibrated, cut, filled, rolled, and placed in trays. The technical specifications emphasize that the seam of the rolled product must be at the centre of the bottom, and the length of the product before being placed in trays must not be less than 19 cm [33]. These practical requirements indicate that the product's shape and the dough's mechanical stability are important even before proofing. If the dough is too sticky, too soft, or too weak, this can complicate shaping, cause uneven distribution of the filling, or result in deformation of the shape. The proofing conditions in a similar process are a temperature of 37°C, 70% relative humidity, and a duration of approximately 70–75 minutes [33]. Such conditions are suitable for standard yeast dough, but it may pose a risk in terms of the stability of a product frozen for 6 months. If the product is proofed too intensively before freezing, its gas cells may become more susceptible to mechanical damage during freezing. In such case, even a properly proofed product may lose structural stability after prolonged storage and after baking exhibit a denser crumb or reduced volume. Therefore, one of the scenarios selected in this study involves not only adjusting the recipe but also the proofing temperature.

Another important aspect is the composition of the used improvers. The specifications for "CO2MMITTED BRIOCHE FREE 5%" improver state that this ingredient is intended for brioche-type products, and its recommended dosage is 5% of the flour weight. The composition includes wheat flour, wheat gluten, pea protein isolate, wheat fibre, potato protein, natural butter flavourings, an enzyme system, and dehydrated acerola concentrate. The enzyme system is listed as maltogenic alpha-amylase, protease, glucoamylase, xylanase, and alpha-amylase [35]. This is particularly important because it indicates that the formulation already contains a functional component capable of acting at the level of the starch, hemicellulose, and gluten systems.

The "PRO-VOLMAX PF" improver specification states that it contains wheat gluten, raising agents E450 and E500, dextrose, wheat flour, emulsifier E472e, milk powder, vegetable oil, acidity regulators E300, and enzymes [36]. This information explains why the approach of increasing the "PRO-VOLMAX PF" content will not be chosen in this study. Since the company's raw material requirements prioritize clean-label ingredients, and E450 is classified as an E additive to be avoided, further increasing the amount of this ingredient could be less appropriate from both a labelling and a customer requirements perspective [34, 36].

Thus, the initial product analysis indicated that the quality issue could be linked to three main areas: water state stability, the efficiency of the enzymatic/structural system, and the control of the proofing process. These three areas formed the basis for the subsequent generation and selection of LLM-based DSS scenarios.

3.3. Development of a Data and Knowledge Base for LLM Based on DSS

Based on the methodology described in Chapter 2, a structured product data and knowledge base was created before using the LLM. This step is essential because the quality of the LLM's response depends directly on the accuracy of the provided context. If the model is presented with only a general question about improving the quality of frozen dough, the response may be too general or fail to account for the actual constraints of the product and the company. Therefore, in this study, the LLM was used only after specific data regarding the product, process, raw materials, and quality issues had been structured.

The DSS knowledge base consisted of five information blocks:

1. product recipe and proportions;
2. a description of the technological process;
3. raw materials and their specifications;
4. the company's requirements for raw material substitution;
5. scientific literature on the degradation of frozen dough quality and possible solutions.

The first set of information was the current product recipe. It allowed us to identify which ingredients were already being used, their proportions, and which parts of the product needed to remain unchanged. This is important because DSS cannot propose solutions that would fundamentally alter the product's identity. In this study, it was decided not to change the lemon cream filling, poppy seeds, surface finish, or the amount of rapeseed oil. The changes were focused on the dough phase, as it is the primary determinant of structure, volume, porosity, and yeast activity.

The second block of information was the technological process. Since a recipe was provided for the new product and the technological process was based on a similar cinnamon-flavoured product, the DSS was provided with information on mixing time, target dough temperature, forming line, filling dosage, proofing temperature, relative humidity, and proofing duration [33]. This block was necessary to ensure that the scenarios were not merely recipe-based but could also account for process variables.

The third set of information concerned the specifications of the raw materials. The specifications for "CO2MMITTED BRIOCHE FREE 5%" improver indicated that this raw material already contains an enzyme system comprising alpha-amylase and xylanase [35]. Therefore, in the DSS scenario selection, the introduction of pure enzymes was replaced with a more practical solution by slightly increasing the amount of the raw material already in use and supplementing it with wheat malt. The "PRO-VOLMAX PF" improver specification indicated that the raw material contains functional ingredients, but also contains E450, which is to be avoided according to the company's requirements [34, 36]. This reduced the priority of increasing the use of this raw material.

The fourth information block consisted of the company's requirements for purchased raw materials. These stipulate that raw materials must not contain GMOs or peanut products, must not contain certain prohibited E additives, partially hydrogenated fats must be avoided, the trans fat content must not exceed 2 g/100 g of fat, and priority is given to clean label raw materials [34]. These requirements served as a practical filter that prevented the selection of solutions that were technically feasible but less suitable for the company's requirements.

The fifth section focused on the literature review based on scientific literature. Reviews of frozen dough emphasize that quality deterioration is associated with yeast damage, weakening of the gluten network, water migration, ice crystallization, and starch retrogradation [22, 23, 26, 27]. Studies on inulin show that it can bind water, reduce its migration in frozen dough, and improve yeast survival [37, 38]. Studies on enzymes indicate that alpha-amylase and endo-xylanase can improve the textural properties of frozen dough and the final baked product [39]. This body of literature has allowed DSS scenarios to be linked to specific mechanisms rather than general claims about recipe improvement. All the sets of information provided beforehand, the content those blocks contained and the functions they serve in DSS are described in Table 9.

Table 9. Information Blocks Prepared for Use with the DSS

Information block	Content used	Role in the DSS process
Formulation of the product	Current ingredients, quantities, and product weight	Defined the base system and the limits of variation
Technological process	Mixing, shaping, proofing, chilling	Allowed for an assessment of the possibility of process adjustments
Raw Material Specifications	Composition of specific raw materials	Helped avoid unnecessary or redundant solutions
Raw material requirements	GMOs, E numbers, clean label, allergens	Served as a practical scenario filter
Scientific literature	Degradation of frozen dough, inulin, enzymes	Provided a mechanistic basis

This structured data preparation is important from a methodological perspective. It demonstrates that the LLM is not used as a free-form generative tool, but rather as part of a controlled DSS architecture. This reduces the risk that the model will propose solutions that sound scientifically sound but are unsuitable in a real-world production context.

3.4. Implementation of an LLM-based DSS and Documentation of GenAI Usage

In this study, the LLM was used as a tool to assist in structuring solutions and generating scenarios. Its purpose was to process the provided product context, link recipe and process variables to the mechanisms of frozen dough degradation described in the literature, and propose technologically sound scenario directions. The LLM was not used as a primary scientific source and was not considered an independent decision-maker for technological solutions. The final scenarios were selected by a human based on product technology, raw material specifications, company requirements, and scientific literature. Since a generative artificial intelligence tool was used in this work, its use must be clearly documented in the text itself, the reference list, and the appendix.

According to general academic citation guidelines, when using GenAI, it is necessary to specify the purpose for which the tool was used, the type of query submitted, the nature of the response received, and how the final text or solutions were verified by a human [40]. Therefore, in this work, the use of ChatGPT is documented not as scientific evidence, but as part of the DSS scenario generation process [41].

LLM received a structured inquiry summarizing that the frozen baked good under investigation, “Lemon Curd Poppy Seed Loaf”, does not withstand a 6-month frozen storage period, the inquiry included the current recipe, the product’s mass proportions, the technological process of a similar product, requirements for raw material substitutions, and specifications for the specific raw materials used. The inquiry requested the development of several solution scenarios, some of which should be based solely on recipe modifications, while others should involve a combination of recipe and process adjustments. The LLM’s response proposed several possible approaches - correction of the sugar system, management of water migration via inulin or other hydrophilic components, optimization of the fermentation system, strengthening of the gluten system, correction of the proofing regime, and control of the cooling process [41].

It is important to emphasize in this work that the suggestions generated by the LLM were not directly accepted as final solutions. They were reviewed and narrowed down based on four criteria: technological feasibility, raw material suitability, industrial feasibility, and experimental verifiability. For example, scenarios proposing the use of pure trehalose, maltodextrin, or separate pure enzyme systems were rejected, as such solutions would be less straightforward in terms of procurement, labelling, and implementation. Instead, industrially simpler alternatives were chosen like glucose syrup, inulin, wheat malt, and an adjustment to the amount of existing “CO2MMITTED BRIOCHE FREE 5%” improver.

This approach to using the LLM aligns with the human-in-the-loop principle described in Chapter 2. The LLM functioned as a layer for generating and justifying scenarios, but the human remained responsible for interpreting and filtering the scenarios and for finalizing the experimental plan. This approach is important not only for academic transparency but also for the food industry’s accountability - decisions that could affect product quality, safety, labelling, or customer requirements cannot be delegated to an autonomous generative model. Documentation of used LLM can be found in Appendix 1.

3.5. Scenario Generation, Filtering and Final Selection

During the initial phase of DSS implementation, several technological approaches were considered. These were linked to specific mechanisms of quality loss in frozen yeast dough. The first approach was water state management, as water migration and ice crystal formation are identified in the literature as some of the main factors contributing to the deterioration of frozen dough quality [22], [23, 26]. The second area was the preservation of yeast viability and enzymatic activity, as yeast damage after freezing can result in lower volume and a denser structure [22, 27]. The third approach was the management of the gluten network and the enzymatic system, as the gluten structure may change during freezing and enzymes can help improve the stability of texture and softness [27, 39]. The fourth area was the adjustment of the proofing process, as overly intense proofing prior to freezing can increase structural fragility.

After conducting a preliminary analysis, it was decided not to select too many scenarios. Although DSS could generate more alternatives, it is important to maintain experimental clarity in the practical part of this study. Too many scenarios would complicate production, storage, analysis, and the interpretation of results. Therefore, three scenarios were selected for the final experiment - a control scenario, a scenario involving only a change in the recipe, and a scenario involving changes to both the recipe and the process. The control scenario K0 is necessary as a baseline for comparison, without it, it would not be possible to objectively assess whether the experimental changes yield benefits. For K0, the current recipe and current process parameters are retained.

Scenario S1 was selected as the formulation modification scenario. In this scenario, part of the sugar is replaced with glucose syrup, inulin is added, and the water content is slightly reduced. This scenario focuses on managing water migration and moisture stability. Glucose syrup was chosen as a commonly used industrial raw material that can help adjust water activity and the sensation of softness. Inulin was chosen as an alternative to pure trehalose or maltodextrin because it is a commonly used food ingredient, can be declared as a dietary fiber, and is associated in the literature with water binding in frozen dough [37, 38].

Scenario S2 was selected as the recipe and process modification scenario. In this scenario, part of the flour is replaced with wheat malt, the amount of "CO2MMITTED BRIOCHE FREE 5%" improver is slightly increased to 5%, and the proofing temperature is reduced. This scenario focuses on managing the stability of the enzymatic system and the process.

Since the "CO2MMITTED BRIOCHE FREE 5%" improver already contains enzymes, including alpha-amylase and xylanase, adjusting its amount is a simpler and more realistic approach than introducing individual enzymes [35]. Wheat malt was selected as a technologically simpler means of gently adjusting amylase activity. Process adjustment was chosen to reduce the risk of overly intense mashing prior to freezing. Summary of the chosen scenarios can be found in Table 10.

Table 10. The Logic Behind the Selection of Final Experimental Scenarios

Scenario	Type	Main changes	Probable mechanism	Reason for selection
K0	Control	Current recipe and process	Base quality is determined	A basis for comparison is required
S1	Formulation changes	Part of the sugar is replaced with glucose syrup, inulin is added, and the water content is reduced	Reducing water migration, stabilizing softness and moisture	Simple, realistic, based on literature and previous practice
S2	Formulation and process parameters changes	Wheat malt, higher "CO2MMITTED BRIOCHE FREE 5%" improver content, lower mashing temperature	Management of fermentative activity and structural stability	Enables an assessment of the value of the integrated solution

This three-scenario structure allows us not only to compare product quality but also to test the methodological principle of DSS. If S1 yields an improvement, it can be concluded that the formulation adjustment focused on the water state is sufficiently effective. If S2 yields a greater improvement, this would indicate that the product issue is not solely formulation related but involves the interaction between the formulation and the process. If neither S1 nor S2 achieves an improvement, one should return to the DSS cycle and test other hypotheses, such as the freezing curve, fluctuations in storage temperature, or the effect of the filling on the dough structure.

3.6. Formulations and Technological Justification of Experimental Scenarios

All experimental recipes are formulated based on 100 kg of flour. This structure allows for a direct comparison between the control and modified formulas. To maintain the product's identity, the following components remain unchanged: lemon cream filling, ground blue poppy seeds, surface glaze and rapeseed oil. The changes focus on the dough system, as it is this system that determines the product's volume, porosity, softness, and stability after freezing.

3.6.1. K0, Reference Formulation

The reference formula, shown in Table 11, corresponds to the current product. It is used as a baseline for comparison.

Table 11. K0, Reference Formulation

Raw material	**Amount, kg / 100 kg of flour**
Flour C-550	100,000
White sugar	15,220
Salt	1,740
Wheat gluten	1,500
CO2MMITTED BRIOCHE FREE 5 % improver	4,960
Yeast	6,960
PRO-VOLMAX PF improver	4,000
Rapeseed oil	18,000
Lemon cream filling	40,847
Ground blue poppy seeds	3,928
Surface glaze	2,357
Water	44,000
Total	**243,512**

The K0 scenario allows us to assess the limits of the current system. Since the recipe already contains gluten, improvers, and a relatively high fat content, we can assume that the problem is not simply a "lack of improvers". It is more likely that the lack of quality stability is related to the state of the water, fermentation stability, or process conditions. Therefore, K0 is used not only as a control but also as a baseline for causal comparison.

3.6.2. S1 - Change in the Formulation

In Scenario S1, shown on Table 12, part of the sucrose is replaced with glucose syrup, inulin is added and the water content is reduced. This scenario is based on the assumption that, during 6 months of freezing, one of the main mechanisms of quality loss is water migration and insufficient moisture stability.

Table 12. Formulation S1 - Correction of the Sugar System and Water Balance

Raw material	Amount, kg / 100 kg of flour
Flour C-550	100,000
White sugar	11,5
Glucose syrup	4,5
Inulin	2,0
Salt	1,740
Wheat gluten	1,500
CO2MMITTED BRIOCHE FREE 5 % improver	4,960
Yeast	6,960
PRO-VOLMAX PF improver	4,000
Rapeseed oil	18,000
Lemon cream filling	40,847
Ground blue poppy seeds	3,928
Surface glaze	2,357
Water	42,5
Total	**244,792**

The inclusion of glucose syrup in this scenario serves several purposes. First, it alters the sugar system and may affect water activity. Second, it can improve the perceived softness and moistness after baking. Third, it can help reduce the mobility of the free water fraction. This is important in the case of frozen yeast-raised baked goods, as water migration and ice crystal growth are associated with structural damage [22, 23, 26]. Inulin was chosen as a simpler alternative to pure cryoprotective agents. Theoretically, trehalose or maltodextrin could be considered, but from an industrial perspective, such raw materials may be less common, more expensive, or less favourable for product labelling purposes. Inulin, particularly chicory fiber, is a more widely used food ingredient and may have a positive effect on water status. In an article "Role of inulin in dough and bread during freezing storage" by Yang et al. it is found that short-chain and long-chain inulin in frozen dough can bind more water, reduce water migration, and improve yeast viability [37]. An article "Effect of long-chain inulin on the rheological properties, water state, gluten structure, and microstructure of frozen dough" by Peng et al. also demonstrated that long-chain inulin can influence water status, rheological properties, gluten structure, and microstructure in frozen dough [38].

Reducing the water content in scenario S1 is necessary because the glucose syrup itself contributes some water, and inulin can alter the dough's water binding balance. If the water content were not adjusted, the dough could become stickier and more difficult to handle on the forming line. Therefore, the water content is reduced from 44.0 to 42.5 kg per 100 kg of flour. This reduction is conservative, it is not large enough to significantly alter the dough's consistency, but sufficient enough to compensate for some of the water contributed by the syrup and the hydrophilic effect of inulin.

3.6.3. S2 - Change in Recipe and Process

Scenario S2 is more extensive because it involves changes not only to the recipe but also to the proofing regimen - process. In the recipe, 0,5 kg of flour is replaced with wheat malt, and the amount of “CO2MMITTED BRIOCHE FREE 5%” improver is increased from 4,96 to 5,10 kg per 100 kg of flour base as seen in Table 13.

Table 13. Formulation S2 - Adjustment of the Fermentation System and Process Stability

Raw material	**Amount, kg / 100 kg of flour**
Flour C-550	99,50
Wheat malt	0,50
White sugar	15,22
Salt	1,74
Wheat gluten	1,50
CO2MMITTED BRIOCHE FREE 5 % improver	5,10
Yeast	6,96
PRO-VOLMAX PF improver	4,00
Rapeseed oil	18,00
Lemon cream filling	40,847
Ground blue poppy seeds	3,928
Surface glaze	2,357
Water	44,00
Total	**244,792**

The essence of this scenario is not an aggressive increase in enzymes, but a gentle adjustment of the existing enzymatic system. The “CO2MMITTED BRIOCHE FREE 5%” improver’s specification states that the recommended dosage of this raw material is 5% of the flour weight, while in the current recipe it is 4,96 kg per 100 kg of flour [35]. Therefore, an increase to 5,10 kg is minor and remains technologically safe. Since the raw material already contains maltogenic alpha-amylase, protease, glucoamylase, xylanase, and alpha-amylase, such an increase allows for the enhancement of enzymatic activity without introducing new pure enzymes [35]. Wheat malt is included as a more natural and industrially simpler means of adjusting amylase activity. Amylase activity may be relevant to the quality of frozen baked goods, as it is associated with starch degradation, the availability of fermentable sugars, and the stability of softness. In an article by KIM, Hye-Jin; YOO and Sang-Ho “Effects of Combined α-Amylase and Endo-Xylanase Treatments on the Properties of Fresh and Frozen Doughs and Final Breads” it is demonstrated that the use of α-amylase and endo-xylanase can improve the textural properties of frozen dough and final baked goods [39]. However, this study does not employ the dosing of pure enzymes but rather an industrial alternative that better aligns with production realities.

In the S2 scenario of the process, the proofing temperature is reduced. In the control process, the proofing temperature is approximately 37 °C, the relative humidity is 70%, and the duration is 70–75 minutes [33]. In the S2 scenario, it is proposed to reduce the proofing temperature to 34–35 °C, maintain relative humidity at 70–75%, and keep the proofing time similar or extend it by up to 5 minutes, depending on the product dimensions. This adjustment aims for a slower, more uniform, and less aggressive dough rise prior to freezing. This could reduce the risk of over-stretching in the gas cell structure and improve resistance to the mechanical stress caused by freezing.

3.7. Experimental Study Plan and Production Process

The experimental study is designed as a comparison of the three scenarios shown in Table 14 - K0, S1, and S2. The primary objective is to determine whether the scenarios generated by the LLM-based DSS can improve product quality stability during a 6-month frozen storage period and to see how can LLM-based DSS system improve product development and shorten its cycle.

Table 14. Subjects of the Experimental Study

Scenario	Formulation	Process	Main objective
K0	Existing formulation	Existing process parameters	Set a quality control level
S1	Part of sugar replaced with glucose syrup, added inulin and reduced water content	Existing process parameters	Assess the impact of the formulation adjustment alone
S2	Added wheat malt, increased content of "CO2MMITTED BRIOCHE FREE 5%" improver"	Lower proofing temperature and slightly increased proofing time	To evaluate formulation and process changes impact

All experimental batches must be produced under identical conditions, as far as the production environment allows. This means that the same mixing equipment, the same forming line, the same filling method, the same amount of lemon filling, the same amount of poppy seeds, and the same final baking mode must be used. The only variables should be those specified in the scenarios. The production process includes the following stages - weighing of raw materials, dough mixing, dough shaping, lemon filling dosing, product rolling, proofing, surface finishing, poppy seed sprinkling, quick freezing, frozen storage, thawing, baking, and quality assessment. At each stage, it is necessary to record the key process parameters, as they are used to interpret the results.

The proofing stage is particularly important. In scenarios K0 and S1, the current proofing regime is applied. In scenario S2, the temperature is reduced to 34-35 °C, while the duration is kept similar or extended to 5 minutes. The purpose of this change is not to reduce the final rise of the product, but to alter the proofing dynamics. In other words, the aim is for the product to reach the desired dimensions more slowly and evenly, thereby reducing the risk of structural over-proofing prior to chilling.

Table 15. Controlled Process Parameters

Stage of the process	Controlled parameter	Importance
Mixing	Mixing time, dough temperature	Affects the gluten network and yeast activity
Forming	Dough strip thickness, product length, width	Ensures uniform geometry
Filling dosage	Filling weight per product	Affects moisture balance and product weight
Proofing	Temperature, humidity, time, dimensions	The critical stage of structure formation
Shock-freezing	Core temperature, freezing time	Affects the formation of ice crystals
Frozen storage	Temperature stability	Affects the risk of recrystallization
Thawing	Duration and conditions	Promotes tissue regeneration
Baking	Time, temperature	Ensures the comparability of results

All the scenarios should be produced in at least two replicates. Replicates are necessary to distinguish the actual effect of the scenario from random production variations. If, due to production conditions, replicates cannot be performed, this must be clearly stated as a limitation of the study.

3.7.1. Quality Assessment Methods

The study is planned with a three-level quality assessment: physical-technological, structural, and sensory. Such approach was chosen because sensory analysis alone cannot explain why a specific scenario works or does not work. On the other hand, structural analysis alone does not reveal whether a consumer or a technologist would rate the product as better. Therefore, a combination of several methods is necessary. Physical and technological indicators include product weight, length, width, height after proofing, height after baking, baking loss, and visual defects.

These indicators allow us to assess whether a scenario affects the stability of the product's volume and its ability to retain its shape. For example, if scenario S2 resulted in a greater product height and a more uniform shape after 6 months compared to K0, it could be concluded that the adjustments to the recipe and proofing regimen helped maintain a better structure.

The ImageJ program is going to be used for structural analysis. This kind of method will evaluate crumb porosity, pore count, average pore size, and the uniformity of pore distribution. The mentioned method is particularly suitable for the study of frozen yeast-raised baked goods, as the pore structure often deteriorates during freezing. Digital texture analysis of baked goods is regarded in the literature as a practical and relatively inexpensive method that can help to compare the structure of baked goods more objectively [28].

Sensory analysis is conducted using a 9-point hedonic scale, evaluating softness, perceived moisture, texture acceptability, aroma, and overall acceptability. The evaluation procedure must be organized in accordance with ISO 13299:2016, ISO 6658:2017 and ISO 8586:2023 [10, 30, 31]. Samples must be coded, presented in random order, and evaluated under uniform conditions. This procedure is necessary to minimize assessor bias.

Table 16. Quality Assessment Indicators and Their Relationship to Scenario Mechanisms

Indicator	Related mechanism	Most relevant scenario
Height after baking	Gas retention, gluten network, yeast	K0, S2
Baking loss	Water retention	S1
Number of pores	Fermentation, gas cells formation	K0, S2
Average pore size	Structural stability	S2
Total porosity	Bulk density and structure	S1, S2
Softness	State of water, starch retrogradation	S1
Perception of moisture	Water migration	S1
Overall Acceptability	Integration of All Features	All Scenarios

The evaluation criteria must be directly linked to the mechanisms of the scenarios. For example, scenario S1 should be considered successful if, after 6 months of storage, the moisture content and softness improve and the density of the structure decreases. Scenario S2 should be considered successful if porosity, rise after baking, and texture uniformity improve. In this way, results will be interpreted not merely according to the “better/worse” principle, but according to the causal relationship between the decision and the quality mechanism.

The steps performed before the analysis of the experimental results indicates the real possibility of applying the developed methodological framework from Chapter 2 to a real industrial product. Firstly, the practical problem was low quality consistency of the "Lemon Curd Poppy Seed Loaf" over a period of 6 months of frozen storage. Secondly, the data on the product was obtained and structured, the recipe, the technological process, raw material composition and its substitutes, as well as the literature base. This information served as the basis for the input into the LLM-based DSS.

The application of LLM within the scope of the work is considered as a part of the scenario generation as an auxiliary stage, but not as the scientific proof on its own. The resulting suggestions were selected and analysed by a technologist, which led to three scenarios being chosen - control K0, recipe change S1, recipe and process change S2. Thus, the current study provides the opportunity to evaluate not only the quality of the final product, but also how effective the LLM-based DSS works in terms of reducing the decision-making search space.

These scenarios have an obvious relation to the processes affecting the quality of frozen yeast dough. Scenario S1 is based on the regulation of the water stability by means of glucose syrup and inulin. Scenario S2 deals with the regulation of the fermentation regime and process of production by means of adding wheat malt and slight increase of "CO2MMITTED BRIOCHE FREE 5%" improver at a reduced proofing temperature.

3.8. Visual Evaluation of Experimental Products

After the production of the experimental batches, samples K0, S1, and S2 were frozen and stored for 4 months. After completion of this storage period, the products were thawed and baked to test how well the recipes used for the control batch and the chosen scenarios on the basis of the LLM-DSS will maintain product quality after a prolonged, 4-month frozen storage. This evaluation was performed 4 months after freezing and it represents an interim verification stage in the study. In terms of technological capabilities, it helps to find out the direction of possible changes in product quality during 6 months of storage, and the technological potential of the scenarios developed.

Extra explanation is necessary in view of methodology. The data collected at this stage reflect its condition after 4 months of storage. Thus, we can say that it is too early to state that some scenarios have totally proven their stability for 6 months. Rather, it should be stated that the results of experimental verification conducted 4 months after storage revealed that certain scenarios developed using LLM-DSS are best able to preserve the structure and quality characteristics of the product until the end of the shelf life which can already show which options are viable.

The visual inspection was performed first, because it allows to see if there is any technical flaw that can be detected due to alterations to the formula and production process. The general form of the product, its surface colour, presence of the filling, arrangement of poppy seeds, consistency of the dough strings, deformations, cracks, and the presence of filling leakage were inspected.

Appearance of baked goods after 4 months of frozen storage and baking can be seen in Figures 6, 7 and 8:

Fig. 7. S1 – Formulation Changes Scenario After Baking

Fig. 8. K0 - Control Scenario After Baking

Fig. 6. S2 – Formulation and Process Changes Scenario After Baking

In terms of appearance, all three products possessed the visual feature common to this kind of product with elongated form, swirled dough structure, spots of lemon filling, and sprinkles of ground blue poppy seeds. This shows us that there were no incompatibilities caused by any of the chosen scenarios from the technological issues point of view. This is very important since the industrial feasibility is one of the requirements set for the LLM-DSS scenarios. The reason is that although some scenarios could be scientifically valid, they would not be feasible in practice if they caused sticky dough, bad forming properties, filling migration, and instability of the product surface.

The appearance of the control sample K0 shown in Fig. 8 is satisfactory over the storage period of 4 months under frozen conditions. However, based on the visual aspects only, it is impossible to make a conclusion about the quality of its internal structure. The external appearance can be satisfactory when the product is frozen, while in a cross section, it might possess such features as structural irregularities, bigger voids, denser dough zones, or uneven distribution of filling and dough.

After 4 months of storage under frozen conditions, the S1 from Fig. 7 scenario product exhibited a relatively stable surface and a satisfactory enough shape. Given the nature of changes made to the S1 product which included a partial replacement of sucrose by glucose syrup, the addition of inulin, and a decrease in moisture content, it became necessary to check whether these factors did any changes to the forming and baking properties. Based on the results obtained, it can be said that the technological compatibility of the S1 changes with the technological process remain satisfactory. There were no signs of shape distortion or significant surface instability noted. As for the S2 sample in Fig. 6, it also showed a satisfactory shape but was noticeably denser and better structured. It is understandable from the technological point of view, as a lowering of the temperature of the dough proofing process and the slight enhancement of the fermentation system were not aimed at maximizing the product volume, but at minimizing the possibility of overly powerful structural stretching before the freezing process. The described approach can prove effective for frozen yeast-raised products because the more stretched gas cell structure is prone to physical damage due to freezing [22, 26, 27].

A preliminary visual assessment allows us to say that both scenarios proposed by the LLM-DSS were applicable under real-world production conditions. They preserved the product's identity and did not cause any visible defects. Therefore, indicators of internal structure and sensory acceptability become the most important factors for further evaluation.

3.9. Analysis of Product Structure Using ImageJ program

The inner structure of the products was estimated based on the ImageJ software analysis. It was selected as the best way for analysing the changes because loss of product quality during freezing can be observed from its inner structure -the number of pores, their sizes, and uniformity of pores distribution. In literature articles, the mentioned changes are often associated with decreased yeast activity, damage to the gluten network, water migration, recrystallization of ice crystals, and starch retrogradation [22], [23], [26], [27]. For each scenario, two samples were used for further analysis, that is, K0 cut 1 (Fig. 9) and K0 cut 2 (Fig. 10), S1 cut 1 (Fig. 11) and S1 cut 2 (Fig. 12), and S2 cut 1 (Fig. 13) and S2 cut 2 (Fig. 14). For each sample, one typical area in the inner part of the crumb was taken, processed using the ImageJ program, and analysed based on the parameters of particles. In this work, parameters of particles provided by ImageJ software can be seen as the differences between structures of slices.

The views of products cuts after baking:

Fig. 9. K0 Cut No. 1

Fig. 10. K0 Cut No. 2

Fig. 11. S1 Cut No. 1

Fig. 12. S1 Cut No. 2

Fig. 14. S2 Cut No. 1

Fig. 13. S2 Cut No. 2

The view of products cuts after baking and processing with ImageJ program, before selection of analysis section:

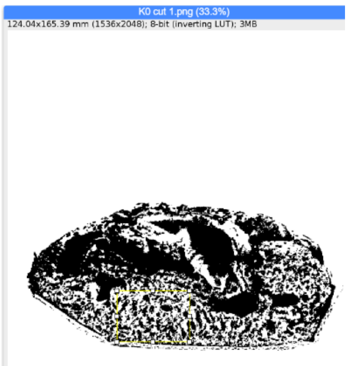

Fig. 15. K0 Cut No. 1 Processed Before ImageJ Analysis

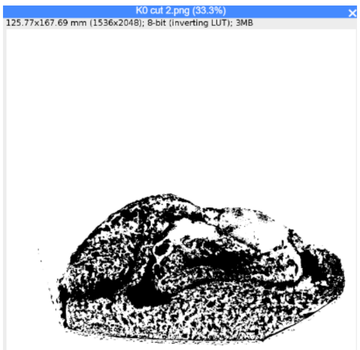

Fig. 17. K0 Cut No. 2 Processed Before ImageJ Analysis

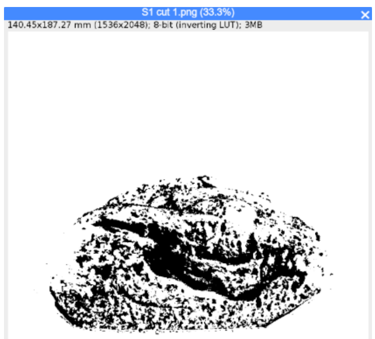

Fig. 16. S1 Cut No. 1 Processed Before ImageJ Analysis

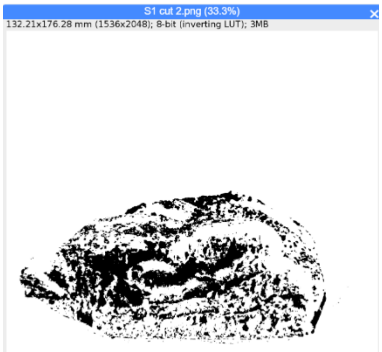

Fig. 18. S1 Cut No. 2 Processed Before ImageJ Analysis

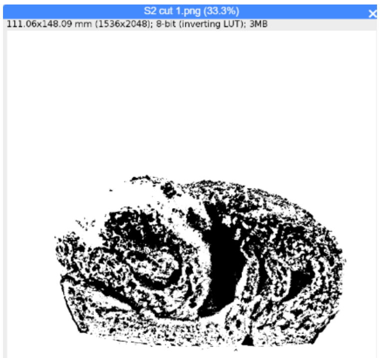

Fig. 19. S2 Cut No. 1 Processed Before ImageJ Analysis

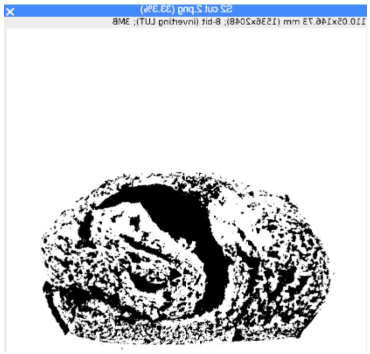

Fig. 20. S2 Cut No. 2 Processed Before ImageJ Analysis

The cross-sectional areas of products selected for ImageJ analysis and the binarized images:

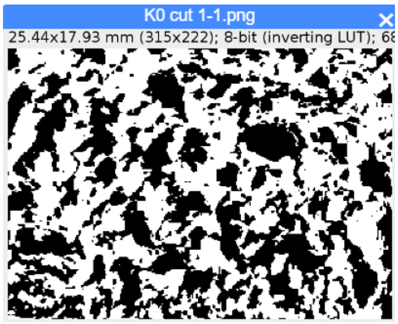

Fig. 23. K0 Cut No. 1 Selected Part for Analysis

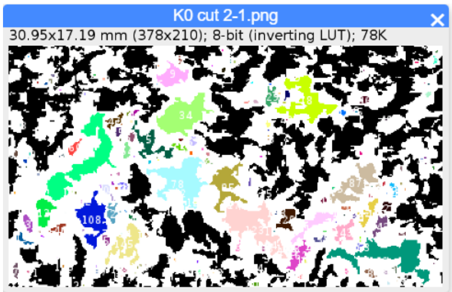

Fig. 22. K0 Cut No. 2 Selected Part for Analysis

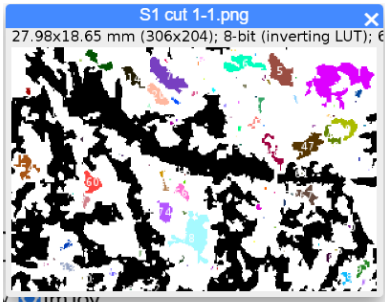

Fig. 21. S1 Cut No. 1 Selected Part For Analysis

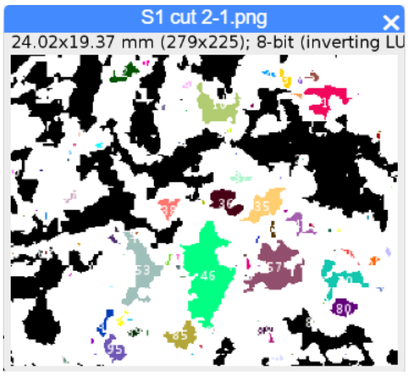

Fig. 25. S1 Cut No. 2 Selected Part for Analysis

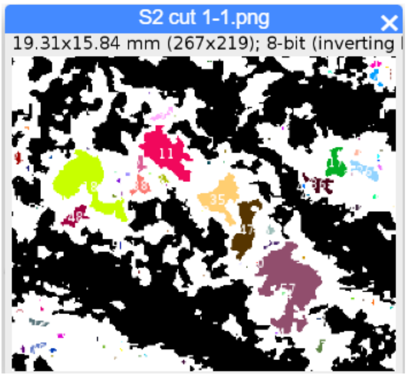

Fig. 24. S2 Cut No. 1 Selected Part for Analysis

Fig. 26. S2 Cut No. 2 Selected Part for Analysis

The following metrics were used in the ImageJ analysis:

– Count - the number of structural objects detected.

– Total Area - the total area of the detected objects.

– Average Size - the average size of a single detected object.

– %Area - the proportion of the area of the detected objects relative to the entire analysed area.

– Feret and MinFeret - the maximum and minimum diameters of the objects, characterizing their extent and shape.

After running the ImageJ program to analyse the selected part of each product's cut the calculations were run automatically as well as results were summarised automatically in the program. After the analysis of each product and each cut all the results were summarised for comparison in Table 17.

Table 17. Results of ImageJ Analysis of Product Structure Based on Individual Sections After 4 Months of Frozen Storage

Scenario	Test No.	Count	Total Area (mm^2)	Average Size (mm^2)	%Area	Feret (mm)	MinFeret (mm)
K0	cut 1	155	80,397	0,519	17,629	0,743	0,411
K0	cut 2	202	83,079	0,411	15,611	0,691	0,392
S1	cut 1	103	43,595	0,423	8,353	0,788	0,439
S1	cut 2	103	49,566	0,481	10,657	0,779	0,443
S2	cut 1	88	28,207	0,321	9,226	0,577	0,324
S2	cut 2	76	25,912	0,341	5,262	0,636	0,378

For the results seen in Table 17 for calculations of average values of each scenario arithmetic mean formula was used in the program:

$$\bar{x} = \frac{x_1 + x_2 \ldots + x_n}{n} \tag{1}$$

where: x is the value of each measurement of pore size; n is the number of variables there are.

Because two separate cuts have been considered in each scenario, the findings can be used as descriptive statistics. This helps us know the trend in structural changes, however, the data is not fully enough to show statistical significance. However, in applied product development studies, the findings are very useful since they help compare the effect of scenarios based on sensory data.For all the scenarios analysed and the results received standard deviations were calculated using this formula:

$$s = \sqrt{\frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 \ldots + (x_n - \bar{x})^2}{n-1}} \tag{2}$$

where: x is the value of each measurement of pore size; n -number of variables there are; x̄ -average mean;

Table 18. Means and Standard Deviations of ImageJ Metrics By Scenario

Scenario	Count	Total Area (mm^2)	Average Size (mm2)	%Area	Feret	MinFeret
K0	178,5 ± 33,2	81,738 ± 1,896	0,465 ± 0,076	16,620 ± 1,427	0,717 ± 0,037	0,401 ± 0,013
S1	103,0 ± 0,0	46,580 ± 4,222	0,452 ± 0,041	9,505 ± 1,629	0,784 ± 0,006	0,441 ± 0,003
S2	82,0 ± 8,5	27,060 ± 1,623	0,331 ± 0,014	7,244 ± 2,803	0,606 ± 0,042	0,351 ± 0,038

Also, to be able to clearly compare the generated scenarios S1 and S2 results with the control K0 percentage change was calculated of those generated scenarios using this formula:

$$\varDelta\% = \frac{x_{scenario} - x_{K0}}{x_{K0}} \times 100 \quad (3)$$

where: $\varDelta\%$ - change percentage of selected measurement of selected scenario compared to K0; $x_{scenario}$ -value of comparable measurement of selected scenario;

Table 19. Change in ImageJ Metrics Compared to K0

Indicator	S1 change compared to K0, %	S2 change compared to K0, %
Count	-42,3	-54,1
Total Area	-43,0	-66,9
Average Size	-2,8	-28,8
%Area	-42,8	-56,4
Feret	+9,3	-15,4
MinFeret	+9,8	-12,6

The comparison of K0 and S1seen in Table 18 and Table 19 reveals that Count dropped from 178.5 to 103.0, that is, by 42.3%. The value of Total Area fell from 81,738 to 46,580, or by 43.0%. Similarly, the %Area dropped from 16,620 to 9,505, that is, 42.8%. Meanwhile, the Average Size fell by just 2.8%. These findings suggests that S1 did not form a too compact structure. Instead, it shows that S1 diminished the number of excess voids and made the structure more uniform, without making it too dense and crumb-like, thus allowing softness formation. Therefore, the findings fit into the technological rationale for S1 scenario. Glucose syrup and inulin were used not for flavour correction, but as means of improving water handling. Inulin is known in the scientific literature to increase the dough hydration, reduce water migration, and enhance yeast survival in frozen dough [37]. Moreover, studies of the impact of long-chain inulin suggest that it influences rheology, water relations, gluten microstructure, and overall microstructure [38]. Thus, structural outcomes of S1 after 4-month storage indicate the success of water management strategy.

The impact of the S2 scenario was even more noticeable as seen from Table 18 and Table 19. Count reduced to 82.0, Total Area to 27,060, Average Size to 0.331, and %Area to 7.244. In comparison with K0, Count was reduced by 54.1%, Total Area by 66.9%, Average Size by 28.8%, and %Area by 56.4%. It means that the scenario S2 generated the most efficient crumb, which was compact and structurally controlled. There were two reasons for the achievement of such an excellent result - moderate tuning of the fermentation system and a low-proofing temperature. As the S2 formulation include "CO2MMITTED BRIOCHE FREE 5%" improver, a fermentation system with the ability to produce amylase and xylanase enzymes, wheat malt may contribute to amylase production [35], [39]. These results have to be interpreted according to the type of product we have. In a filled, rolled yeast-raised product, a large area of detected pores or voids does not necessarily indicate better quality. On the contrary, large, irregular voids may be associated with structural instability, uneven gas retention, or problems with the interaction between the filling and the dough. Therefore, the highest K0 %Area value is not automatically considered a quality advantage. Since the sensory results for K0 were weaker, a larger area of detected voids is more likely to be interpreted as a sign of a less controlled structure. S1 is evaluated as the most balanced structural scenario. It reduced the total area of detected objects but did not result in strong crumb compaction. S2, in contrast, reduced the area of pores/voids and the average object size the most. This indicates stronger structural stabilization, but at the same time carries the risk that the product may be perceived as less soft. Therefore, the ImageJ results must be evaluated in conjunction with the sensory analysis data.

3.10. Sensory Analysis and Results After 4 Months of Frozen Storage

A sensory evaluation has been carried out in order to find out how the changes of the recipe and process influence the perception of quality after 4 months of storage in frozen state. The importance of such assessment can be explained by the fact that purely structural characteristics are not enough to prove that the product will be accepted by consumers. As it was mentioned before, the quality of this type of product is determined not only by its porous structure but also by other aspects including moisture content, tenderness, smell and texture. The total number of participants in sensory evaluation amounted to 20 people - 15 technologists and 5 consumers. Such a combination of experts' profiles can be justified by the fact that technologists are usually able to notice various signs of structure and defects in filling, while consumers provide a generalized assessment of product quality. Such combination is appropriate for practical food technology research aimed at determining practical features of the product. Analysis was done on the basis of the 9-point hedonic scale which was previously shown in Table 7.

In the case of the 9-point scale, 1 corresponds to “Dislike very much,” 5 corresponds to “neither like nor dislike,” and 9 corresponds to “Like very much.” The 9-point scale is very common in the area of consumer acceptability research and helps to easily compare different product varieties [42]. Sensory analysis was carried out according to the recommendations provided by ISO 13299:2016, ISO 6658:2017, and ISO 8586:2023 [10, 30, 31]. The criteria included in the evaluation were: appearance, aroma, tenderness, moisture content, texture acceptance, filling-to-dough ratio, and overall liking. Such criteria were chosen for the evaluation because they relate to the most often occurring quality deficiencies of yeast raised frozen products such as dryness, hardening, poor texture, lack of smell, and decreased acceptance. The sensory results presented below are a summary based on the panel evaluation and the context of the study.

Table 20. Summary of the Results of Sensory Analysis

Criteria	**K0**	**S1**	**S2**
Appearance	6,6 ± 0,9	7,7 ± 0,7	7,5 ± 0,8
Aroma	6,5 ± 0,8	7,5 ± 0,7	7,4 ± 0,8
Tenderness	5,9 ± 1,1	8,1 ± 0,6	7,3 ± 0,8
Moisture feeling	5,8 ± 1,2	8,0 ± 0,6	7,2 ± 0,9
Texture	6,1 ± 1,0	7,8 ± 0,7	7,8 ± 0,7
Filling to dough ratio	6,4 ± 0,9	7,7 ± 0,8	7,5 ± 0,8
Overall liking	6,2 ± 1,1	8,0 ± 0,6	7,7 ± 0,7

Based on the obtained results seen in Table 20, it can be seen that both formulas suggested by the LLM were assessed positively compared to the control formulation. It should be noted that the most noticeable positive change was found in the evaluation of softness and moisture levels of both changed scenarios formulations. For example, the rating for softness of K0 equals 5.9 points, while for S1 - 8.1 points. Similarly, moisture of K0 scenario was evaluated at 5.8 points, while for S1 -8.0 points. Thus, an improvement of +2.2 points is observed in each case. Such result is directly correlated with the purpose of S1 scenario. S1 was created as a water management scenario, where sucrose was partially substituted by glucose syrup, inulin was added to the formulation, and the water level was decreased. Based on this theoretical model, it was thought that it could provide a softer and more moist product after frozen storage, which, indeed, happened at the 4-month storage point based on sensory results. Another scenario, S2, also had an improved assessment compared to K0 control scenario. Its overall acceptability reached 7.7 points, and texture acceptability - 7.8 points. This shows that changes in both formulation and process parameters had a positive impact on product quality. Nevertheless, it should be noted that the softness and moisture assessment of S2 scenario were not as high as for S1. This can be explained by ImageJ data where it can be seen that S2 crumb formation was more compact.

Both groups of sensory evaluators, the technologists and consumers evaluations confirmed that the ranking of the scenarios was consistent as seen from Table 21, with K0 being the worst scenario, S1 being the best, and S2 performing better than the control scenario. The two generated by LLM scenarios, S1 and S2, were evaluated almost equally well by the technologists since S2 was structured more tightly. The users had a definite preference for S1, which is probably because they felt that it offered more comfort and moisture. It is worth noting that technological feasibility and consumer satisfaction may not necessarily correspond with each other. In this context, the value of LLM-DSS lies not only in proposing the "best possible" scenario, but in demonstrating the trade-offs in quality that each scenario entails.

Table 21. Comparison of Overall Acceptability by Evaluator Group

Evaluators	**n**	**K0**	**S1**	**S2**
Technologists	15	6,1	7,9	7,8
Consumers	5	6,5	8,2	7,6
Average	20	6,2	8,0	7,7

Table 22. Change in Sensory Indicators Compared to K0

Criteria	**S1 change, points**	**S2 change, points**
Appearance	+1,1	+0,9
Aroma	+1,0	+0,9
Softness	+2,2	+1,4
Moisture feeling	+2,2	+1,4
Texture liking	+1,7	+1,7
Filling to dough ratio	+1,3	+1,1
Overall liking	+1,8	+1,5

Based on Table 20 and Table 21 results and comparison of results of sensory analysis it can be seen that S1 best met the consumers quality needs. While S2 yielded a strong result in terms of texture acceptability. Both scenarios were better than the control scenario, so it can be concluded that the corrections suggested by the LLM-DSS were technologically applicable and improved sensory attributes under 4-month frozen storage conditions.

3.11. Integrated Evaluation of ImageJ and Sensory Analysis Results

ImageJ analysis in isolation or sensory results in isolation are not enough to accurately explain the influence of scenarios. ImageJ enables to assess the structure of crumbs more objectively, however, it cannot demonstrate whether or not the product looks appetizing to the consumer. On the other hand, sensory analysis shows consumer and technological acceptability but does not always provide us with a chance to see what kind of changes have occurred inside. Thus, both analyses are used concurrently in this study.

As compared in Table 23, according to the performed image analysis, the highest values of Count, Total Area, and %Area belong to the K0 recipe. On the surface, this could be seen as increased porosity. Nevertheless, when talking about filled rolled pastry products, the result above could also mean non-uniformity, bigger voids, etc. As far as the K0 recipe has the lowest sensory results, which lets us say that a higher %Area in this case does not indicate quality features but means low structural stability over 4 months of frozen storage. As compared to K0, the S1 scenario demonstrated lower %Area - it dropped from 16.620 to 9.505, whereas Average Size remained almost identical. It seems like S1 structure became more balanced, but it was not too dense. The sensory data supported the results above because S1 scored the highest points in terms of softness, moisture, and acceptability. Therefore, we can say that this scenario successfully accomplished the objective of water state control. From image and sensory analysis results and Table 23 it can be seen that scenario S2 had the greatest influence on the structure itself since its values of %Area and Average Size were the smallest. Thus, the crumb became the most dense.

This could be seen as positive from the viewpoint of addressing the problem associated with large cavities in the structure of the product. But at the same time, S2 received the worst score regarding softness and moisture in comparison with S1. This means that there is a compromise between achieving good technological structure and obtaining a desired acceptable texture of the product. Such trade-off is a characteristic of food product development, where technological stability and consumer acceptable texture must be balanced rather than evaluated separately.

Table 23. Integrated Comparison of Structural and Sensory Results

Evaluation criteria	**K0**	**S1**	**S2**
ImageJ %Area	16,620	9,505	7,244
Average pore size (mm^2)	0,465	0,452	0,331
Interpretation of the structure	More voids, more uneven crumb structure	Balanced structure	Compact structure
Softness (sensory evaluation)	5,9	8,1	7,3
Moisture feel (sensory evaluation)	5,8	8,0	7,2
Texture acceptability (sensory evaluation)	6,1	7,8	7,8
Overall liking (sensory evaluation)	6,2	8,0	7,7
Overall evaluation	Base, the weakest	Best sensorial and structural balance	Strongest structure control scenario

An integrated evaluation of the image and sensory analysis results shows that both of the scenarios generated by the LLM-DSS model have been successful to some level. Each scenario has achieved success through its own different means. The scenario S1 made the most significant improvements in sensory acceptance, especially in softness and moisture content. On the other hand, scenario S2 made the most significant changes in structure of the product and decreased the areas of voids.

3.12. Evaluation of the Effectiveness of DSS Scenarios

Apart from the correction of a particular recipe for producing the product of this work, a more general task is to determine the ability of an LLM-based system to support decision making to achieve better efficiency of the production process and improve its quality. Consequently, it is not enough to discuss the product results but also it is important to analyse the decision-making process. Initially, various technologies were reviewed - correction of the sugar technology, application of glucose syrup, inulin or other water-attracting materials, pure cryoprotectants, correction of the enzymatic technology, increase of the gluten content, yeast content adjustment, change of proofing regimes, and regulation of the freezing process. All of these options were in some ways promising and correct from a technological point of view, but not all of them were suitable for conducting the industrial experiment. As seen in Table 24 during the expert screening process, the range of scenarios was reduced to two active scenarios and one control scenario. The scenarios were K0 as the baseline scenario, S1 as the formulation modification scenario, and S2 as the formulation and process modification scenario. In this way, it was possible to reduce the number of experiments without losing the methodological approach of control, formulation alone, and formulation plus processing.

Table 24. Logic for the Selection and Validation of DSS Scenarios

Step	Result	Value for the research
Problem analysis	The planned 6-month stability of the frozen product cannot be guaranteed	The problem is related to the stability of water, structure, and fermentation
LLM scenarios generation	Several recipes and process paths have been generated	The speed of the solution search has been increased
Expert screening	Chosen scenarios K0, S1 and S2	The number of unnecessary tests has been reduced
Experimental validation	Performed after 4 months of frozen storage	The potential effectiveness of the scenarios was assessed prior to the final 6-month mark
Interpretation of the results	S1 and S2 outperformed K0	It has been confirmed that the DSS proposals were effective under 4-month storage conditions
Further actions	A 6-month inspection is required	Final shelf-life validation is required

The effectiveness of DSS can also be assessed by narrowing the search space. If six main solutions were considered in the initial stage and two active scenarios were selected for the experiment, the search space was reduced by 66,7%:

$$Search\ field\ reduction = \frac{x_1 - x_2}{x_1} \times 100 \quad (4)$$

Where: x_1 -initially suggested scenarios number; x_2 -number of active scenarios selected for experiment;

$$Search\ field\ reduction = \frac{6-2}{6} \times 100 = 66{,}7\%$$

The presented indicator should not be considered as economic effect result of the organization, but it proves the effectiveness of decision-making. In the process of development of the product, each next test will require the consumption of material, working hours on the production line, the work of employees, the use of freeze storage, and tests in laboratories. The benefit of the application of the LLM-DSS can be considered its ability to shift faster from general problem formulation to limited, logically reasoned, and tested scenarios. Both chosen scenarios gave positive results after four months of frozen storage, which allowed concluding about the usefulness of using LLM-DSS for scenario generation. Scenario S1 confirmed the right direction of water state stabilization, and scenario S2 confirmed the right direction of structure and process control. It allows saying that the developed system not only produced ideas but proposed specific solutions.

3.13. A Technical and Practical Comparison of Scenarios

A final assessment of the scenarios cannot be done only by deciding which scenario has the best sensory attributes. In food production, a broader view of the decision should be taken into account, such as its impact on the quality of the product, ease of implementation, use of proper raw materials, risk in the process, its effect on the lines, and applicability to validate further. K0 is the current formulation in production. Its strength lies in the fact that no adjustment is necessary and it is known by production. After 4 months of frozen storage, K0 was the worst when it comes to sensory assessment and had the most significant area of structural holes detected. From the comparison seen in Table 25 it can be said that among all scenarios considered, S1 has the greatest potential to be adapted from a technological point of view.

From the acquired data, S1 has achieved better results regarding the softness, moisture content, and acceptability of product samples. Moreover, according to ImageJ analysis, the structure of S1 sample has become more balanced. Finally, S1 does not imply a modification of the process mode. It is very important from an operational perspective since any changes in a process mode add to the complexity of management. The risks associated with S1 consist in new raw material specifications, potential dough stickiness, labelling and cost aspects. Scenario S2 may be regarded as an excellent case in terms of technological stability. However, it implies changes in the process mode that include lowering the temperature of the proofing and perhaps extending proofing time. Thus, S2 may be seen as a promising direction for further optimization of the process, but its adaptation will be more complex than that of S1.

Table 25. A Practical Comparison of Scenarios K0, S1, and S2

Criteria	**K0**	**S1**	**S2**
Quality improvement	Does not improve, control scenario	Very high, especially sensory qualities	High, especially structure
Ease of implementation	Very easy	Easy implementation	Intermediate
The need to change the process	None	None	Proofing process change
The need to replace raw materials	None	Glucose syrup and inulin	Wheat malt and “CO2MMITED BRIOCHE 5%” improver amount increase
Sensory acceptability	Lowest	Highest	High
Structural stability according to ImageJ	Lowest	Good balance	The most compact structure
Main risk	Insufficient stability during prolonged storage	Adhesiveness, labelling, price	Process control, potential for greater particle compactness
Recommendation	Use as a control	Top candidate for implementation	A candidate for further optimization

Based on the gathered results from all the analyses, S1 is recommended as the primary candidate for further implementation for a 6-month shelf-life period. S2 is also very valuable, but its implementation should be considered only when the main goal is structural stability or when the proofing parameters will be further optimized.

3.14. Justification of the Results of the 4-month Frozen Storage Trial

Despite the fact that the expected storage time for the experimental product is 6 months, the results achieved within 4 months are important from a methodological view. Such findings do not serve as a final proof of the product's shelf life being 6 months, however, they allow evaluating the correctness of the selected formulation and technological scenarios. The storage time of 4 months comprises two-thirds of the total storage period. In other words, the products were analysed not at an early storage stage, but rather at an advanced stage of storage. If the formulations and technological processes under evaluation had been inadequate, it would be expected to have some quality deterioration seen by then: decreased softness, reduced moisture sensation, uneven or dense crumb, and worse overall product acceptability.

An interim evaluation fits into the framework of the shelf-life assessment process. In shelf-life testing in foods, besides examining the final quality of the sample, quality changes are analysed during the entire storage period [45]. According to ISO 16779:2015, the shelf life of a product can be determined and confirmed taking into account sensory changes that happen during storage [46]. For frozen yeast-raised bread, such an approach is especially fitting because the quality reduction happens gradually due to the following processes: yeast cells die off, the gluten structure becomes unstable, water shifts, and recrystallization of ice crystals occurs [22, 26, 27].

The results of the 4-month research allowed concluding about the significant differences in performance between the three different scenarios. It is evident that Scenario S1, where part of the sugar was substituted by glucose syrup, inulin was added, and the water content was decreased, was the one that showed the best performance regarding softness, moisture, and acceptability. Such a statement corresponds to the existing results in the scientific literature that proved that inulin can positively affect the structure and the quality of frozen dough through reducing water migration, improving water binding properties, and increasing structural stability [37, 38]. Scenario S2, in turn, where the system of enzymatic control was adjusted, and the proofing temperature was changed, had a great influence on the quality of crumb structure, since according to ImageJ results %Area decreased by 56.4% compared to K0.

Thus, it confirms the high level of structural control achieved with the help of this scenario. It should be noted that there are two types of conclusions related to the results obtained. Firstly, as it was shown above, according to the data collected in this study, it can be concluded that after being stored in freezing conditions for 4 months, scenarios S1 and S2 turned out to be significantly more effective in sensory and structural aspects than the control scenario K0. Secondly, such conclusions cannot serve as the confirmation of the effectiveness of the two scenarios over the whole period of 6 months of storage. That is why, in spite of the positive effect obtained after 4 months of freezing, they should be treated as an interim justification of certain decisions. In general, it can be stated that the results of 4-month freezing storage testing are enough to evaluate whether the selected scenarios are technically correct and are effective without waiting for the full 6-month frozen storage period.

3.15. Chapter Summary

The research showed that LLM-based decision support systems could be effectively applied in practice in order to increase the quality of frozen yeast-raised baked goods. In addition to suggesting possible changes in recipes and processes, the model provided information about underlying quality improvement mechanisms related to water migration, crumb structure control, enzymes, and proofing control. According to sensory evaluation performed by consumers, after four months of frozen storage, the quality of products manufactured according to S1 and S2 scenarios was better compared to the control recipe K0. Scenario S1, where some sugar was replaced with glucose syrup, inulin was added to the dough and water was decreased, improved the taste and sensory characteristics more than other recipes. However, in case of S2 scenario, where the change in the recipe combined with decreasing the proofing temperature, the influence on crumb structure control was better but from the point of view of consumer preference it was inferior to S1.

Having analysed the above-mentioned results, it is possible to say that the S1 scenario is the best option that can be recommended to implement since there is no need to change technological process. S2 can also be used if structure control is the main objective. Though the results prove the effectiveness of the scenario for 4 months, further studies should be conducted to provide a conclusion for six months period. Nonetheless, the above-presented data prove that the LLM-DSS can be helpful in structuring quality problems and selecting solutions.

4. Social, Economic, and Environmental Assessment of the Implementation of the LLM-DSS

Apart from checking the effectiveness of recipes and process scenarios in improving quality, the analysis of this chapter covers a wider scope of their significance for food production management. In this regard, given the main goal of this work, LLM-based DSS, the evaluation must include other three aspects, each one being related to other two: economic, managerial and environmental. It is consistent with the concept of Food Quality 4.0 and Food Processing 4.0 according to which control over food quality goes beyond mere verification of its attributes, instead, it is seen as a complex system based on data and processes [19 - 21].

For this project, the object of consideration was a frozen yeast-raised baked good, whose quality needed to be stabilized by using new recipes and process scenarios. After four months of frozen storage, it was found that scenarios S1 and S2 showed better results compared to the control recipe K0. Scenario S1 had most positive effects on the parameters of softness, moisture and acceptability of the tested samples, whereas scenario S2 showed greatest effectiveness in controlling crumb structure. Therefore, the following will evaluate practical significance of these findings.

4.1. The Economic Rationale for Applying LLM-DSS in the Product Development Process

In the case of an enterprise engaged in the production of food products, the solution of a problem connected with the quality of the product often involves conducting several different tests which includes correction of the recipe, analysis of raw materials, alteration of process conditions, taste testing, storage testing, and repeated production runs. Each test takes resources. This is not only the resources of raw materials but also the resources of production time, labour, energy resources, frozen storage space, analysis, and scrap losses. Thus, the efficiency of the decision-making process has a direct impact on the expenses for the creation of new products. The value of the LLM-DSS tool used in this work is mainly manifested in the reduction of the decision-making space. In the first step, six technological ways were analysed: correction of the sugar mixture formula, use of glucose syrup, addition of inulin or other water-absorbing substances, correction of the fermentation regime, reinforcement of the gluten system, and correction of yeast or the proofing process. The LLM-generated alternatives were then filtered by technologists, and two active measures - S1 and S2, and one control measure K0 were selected for the experimental design.

Six main solutions were considered in the initial stage, and two active scenarios were selected for the experiment, the search space was reduced by 66,7% which was calculated using this formula:

$$Search\ field\ reduction = \frac{x_1 - x_2}{x_1} \times 100 \qquad (5)$$

Where: x_1 -initially suggested scenarios number; x_2 -number of active scenarios selected for experiment:

$$Search\ field\ reduction = \frac{6-2}{6} \times 100 = 66{,}7\%$$

This shows that rather than six possible trial runs, the experiment was limited to only two directions which were justifiable. This does not mean that there is an automatic calculation for profit, but this shows a very important advantage for management purposes, the DSS system eliminated those options that were not feasible enough and required complex calculations before conducting the actual tests for production. The result of search field reduction was less unnecessary trial runs, which saves raw materials, and materials required for production runs. Such logic is confirmed by current research in application of AI to food production. Currently, AI solutions applied to food production are often linked to production optimization, waste minimization, quality control, as well as resource utilization [43]. What is important about using AI in such cases is not the model that makes the decision at the end, but its capacity for quick analysis of complicated data and minimization of uncertainty in decision-making [16, 21, 43].

4.2. Assessment of the Cost of Raw Materials Resulting from Changes to the Recipe

To compare the economic impact of the scenarios, the change in the prices of the raw materials was calculated by comparing K0, S1, and S2. The calculations were based on 100 kg of flour, just like in the recipe tables. Since the prices of all raw materials were not necessary to compare the price changes between the scenarios, only those raw materials that differed between the scenarios were evaluated: sugar, glucose syrup, inulin, wheat malt, “CO2MMITTED BRIOCHE FREE 5%” improver, as well as the reduction in flour in the S2 case. Raw material prices used are shown in Table 26:

Table 26. Raw Material Prices Used in the Economic Assessment

Raw material	Price, Eur/kg
Sugar	0,48
Glucose syrup	1,34
Inulin	4,89
Wheat malt	2,46
Yeast	1,07
“CO2MMITTED BRIOCHE FREE 5 %” improver	8,81
“PRO-VOLMAX PF” improver	3,72
Flour C-550	0,28

In Scenario S1, the content of sugar was reduced from 15,22 kg to 11,50 kg, and 4,50 kg of glucose syrup and 2,00 kg of inulin were added. The amount of water was reduced, but the cost of water is not considered significant. Prices of materials used in formulations were calculated using formula:

$$Raw\ material\ used\ in\ formulation\ \ price = amount\ of\ material\ \times price\ of\ material \quad (6)$$

Using the formula for price of materials used in formulations, material prices were calculated and the results can be seen in Table 27. Each scenario contains only the price of the raw materials that differed from the control formulation. Also, prices were calculated only for the materials that were the main drivers for changes in the generated scenarios.

Table 27. Prices of Changed Materials in Each Scenario

Raw material	Price in K0, Eur	Price in S1, Eur	Price in S2, Eur
Sugar	7,31	5,52	7,31
Glucose syrup	-	6,03	-
Inulin	-	9,78	-
Wheat malt	-	-	1,23
"CO2MMITTED BRIOCHE FREE 5%" improver	43,7	43,7	44,93
Total	7,31	21,33	46,16

S1 raw materials price increase compared to K0:

$$21{,}33 - 7{,}31 = 14{,}02 \; Eur\,/\,100\,kg\,flour$$

In Scenario S2, part of the flour was replaced with wheat malt, the amount of flour was reduced from 100,00 to 99,50 kg, and 0.50 kg of wheat malt was added. The amount of "CO2MMITTED BRIOCHE FREE 5%" improver was increased from 4,96 to 5,10 kg.

The cost of adding wheat malt in S2, taking into account the reduced amount of flour:

$$1{,}23 - 0{,}14 = 1{,}09 \; Eur$$

Cost of additional “CO2MMITED BRIOCHE FREE 5%” improver:

$$(5{,}100 - 4{,}960) \times 8{,}81 = 0{,}140 \times 8{,}81 = 1{,}23 \text{ Eur}$$

Total increase in the price of S2 raw materials:

$$1{,}09 + 1{,}23 = 2{,}32 \text{ Eur / 100 kg flour}$$

Table 28. Change in the Price of Raw Materials Under Different Scenarios, Calculated on the Basis of 100 Kg of Flour

Scenario	Main price change	Additional charge, Eur / 100 kg flour
K0	Control formulation	0,00
S1	Less sugar, added glucose syrup and inulin	+14,02
S2	0,5 kg of flour changed with wheat malt, increased amount of “CO2MMITED BRIOCHE 5%” improver	+2,32

According to the standard recipe, approximately 785,52 units of the product are produced from 100 kg of flour. The unit cost is then calculated as follows:

$$Additional\ price\ per\ piece = \frac{\frac{additional\ price}{100kg\ of\ flour}}{785{,}52} \tag{7}$$

In scenario S1 price per piece increase by:

$$\frac{14{,}02}{785{,}52} = 0{,}0179\ Eur/pcs.$$

In scenario S2 price per piece increases by:

$$\frac{2{,}32}{785{,}52} = 0{,}0030 \text{ Eur/pcs.}$$

Table 29. Additional Unit Raw Material Cost by Scenario

Scenario	Price increase, Eur / 100 kg of flour	Price increase, Eur/pcs.	Price increase, ct/pcs.
S1	14,02	0,0179	1,79
S2	2,32	0,0030	0,30

From the above results, from Table 28, it can be seen that formulation wise, S1 is more costly because of inulin, which is quite costly in its basic raw form. Nevertheless, the additional cost incurred for each product is only approximately 1,79 cents. Since the acceptability of S1 improves from 6,2 to 8,0 points, softness increases from 5,9 to 8,1 points, and moisture content perception increases from 5,8 to 8,0 points, this added cost can be justified because of its positive effects.

On the other hand, formulation wise, S2 is the cheaper one. It's cost increase per unit is approximately 0,30 cents. This is a scenario with a change in the process as well, which means that economic analysis in this case cannot be done only through raw material cost consideration. The effect of decreased proofing temperature and perhaps increased proofing time needs to be determined in terms of line speed and proofing capacity.

4.3. Interpretation of Line Capacity and Production Costs

The production line's capacity is 2400 units per hour. This known number makes it possible to estimate what would the additional raw material costs be that each scenario would incur per hour of production if the line was operating at the known capacity.

In scenario S1 the extra cost per hour would be:

$0{,}0179 \times 2400 = 42{,}96$ Eur/h

In scenario S2 the extra cost per hour would be:

$0{,}0030 \times 2400 = 7{,}20$ Eur/h

For a batch of 10000 pcs, the increase in cost would be:

$S1: 0{,}0179 \times 10000 = 179{,}00$ Eur

$S2: 0{,}0030 \times 10000 = 30{,}00$ Eur

It is seen from these calculations that there is a trade-off. S1 is a more expensive formulation but the effect on quality according to sensory criteria was maximum. S2 is a cheaper formulation with respect to material cost, but process changes should be made in this case. Hence, the decision will not only depend upon the material cost but also upon the problem that costs the most to the firm: sensory acceptability, dryness, bad texture, or unstable structure.

In case of S2 formulation, one more important point needs to be taken into consideration. That is proofing time. In case lower temperature needs proofing by 5 more minutes and proofing chamber is the process limiting step, then capacity can fall due to theoretical capacity at this step. If reference proofing time is 75 minutes and S2 formulation will increase it to 80 minutes, then the relative reduction in capacity is expected to be:

$$Capacity\ reduction = \frac{x_1 - x_2}{x_1} \times 100 \tag{8}$$

Where: x_1 -the time required for proofing with the updated process parameters; x_2 -the time required for proofing with existing process parameters;

Therefore:

$$\text{Capacity reduction} = \frac{80 - 75}{80} \times 100 = 6{,}25\%$$

In that case, the theoretical efficiency could decrease:

$$x_1 \times (1 - CR) \quad (9)$$

Where: x_1 -current production capacity; CR -capacity reduction value of proofing;

Therefore:

$2400 \times (1 - 0{,}0625) = 2250$ vnt./h

Considering the analysis above, assuming that proofing is the limiting step, there will be a reduction in line capacity of about 150 pcs/hr. But, if the proofing chamber is not operating at full capacity and S2 can manage to have about the same proofing time as K0, then the line capacity will still remain at 2400 pcs/hr. In other words, this means that the economic feasibility analysis of S2 should be done based on both scenarios.

Table 30. Potential Impact of S2 Process Adjustments on Line Productivity

Case Study	Proofing time	Production capacity	Interpretation
S2 without loss of production capacity	70–75 min.	2400 pcs. /h	The process does not affect the line speed
S2 with a +5-minute delay	about 80 min.	about 2250 pcs. /h	A 6.25% reduction in capacity is possible if proofing is the limiting factor

For this reason, S1 is the easier solution to adopt. It adds to the expense of the raw materials but does not change the process speed. S2 is cheaper in regard to raw materials, but its economic worth will be based on the process flow and proofing chamber capacity.

4.4. The Economic Interpretation of Quality Improvement

The results of Chapter 3 showed that S1 and S2 improved sensory acceptability compared to K0. The overall acceptability score for K0 was 6,2, for S1 it was 8,0, and for S2 it was 7,7. The relative improvement is calculated like this:

$$Sx = \frac{z_x - K0_s}{K0_s} \times 100 \quad (10)$$

Where: Sx -the scenario for which the relative improvement is calculated; z_x -value of x scenarios evaluated criteria from sensory analysis; $K0_s$ - value of K0 scenario evaluated criteria from sensory analysis;
Therefore:

$$S1 = \frac{8{,}0 - 6{,}2}{6{,}2} \times 100 = 29{,}0\%$$

$$S2 = \frac{7{,}7 - 6{,}2}{6{,}2} \times 100 = 24{,}2\%$$

When it comes to the test object S1, the softness parameter grew by 37.3% and the level of moisture by 37.9%. These criteria carry an economic significance because they are one of the main qualities of the frozen dough baked products. Should the product turn out to be dry and hard when thawed and baked, there is the possibility of customers being dissatisfied and returning it back.

Table 31. The Ratio of Quality Improvement to Additional Cost

Citeria	K0	S1	S2
Overall acceptability	6,2	8,0	7,7
Improvement in overall acceptability compared to K0	–	+29,0 %	+24,2 %
Improvement in softness compared to K0	–	+37,3 %	+23,7 %
Improvement in moisture content compared to K0	–	+37,9 %	+24,1 %
Additional raw materials price, ct/pcs.	–	+1,79	+0,30
Practical assessment	Base option / control formulation	Best quality improvement	The most cost-effective quality improvement

As can be seen from the Table 31, S1 is the best quality option, though at the same time it is the most expensive one. On the contrary, S2 is the most economical option, but it is somewhat difficult to realize because of certain changes in the process. Thus, we need to know what priorities have been set by the company. The S1option would be the case when sensory enhancement is the main aim, and if minimal cost increase and stronger texture control is the aim S2 should be chosen.

4.5. Potential for Reducing Waste and Scrap

Defects in the manufacturing of frozen baked products can be caused by incorrect dough composition, shaping problems, inadequate proofing, movement of fillings, poor texture, or unfavourable sensory characteristics after storage. The number of defects on the line in this study was not measured, thus, it is impossible to determine the savings in euros. Nonetheless, quality parameters make it possible to evaluate the potential savings.

According to ImageJ measurements, the two scenarios S1 and S2 minimized the area of detected structural elements. For S1 %Area, the values were 16,620 and 9,505, representing a decline of 42.8%, while for S2, the values were 16,620 and 7,244, showing a decrease of 56.4%. This indicates that both scenarios reduced signs of structural irregularity.

Table 32. The Relationship Between Structural Stability Indicators and Potential Defect Reduction

Criteria	K0	S1	S2
ImageJ %Area	16,62	9,50	7,24
Change compared to K0	–	-42,8 %	-56,4 %
Overall acceptability	6,2	8,0	7,7
Likely practical significance	Higher risk of quality fluctuations	Lower risk of sensory rejection	Lower risk of structural defects

In terms of waste minimization, however, the logic of S1 and S2 is different. For example, S1 may minimize waste because of the higher consumer and sensory acceptability while S2 will do so because of increased structural control. In absence of any real defects, the next step would be to gather data about the total amount of waste, types of waste and consumer complaints. Minimization of food waste is crucial from both economic and environmental viewpoints. From the literature, it can be concluded that using AI technology is useful for the purpose of minimizing waste since AI technologies can better predict quality deviations and make informed decisions [44].

4.6. The Importance of LLM-DSS in the Product Development Phase

This study demonstrates that the potential for value of the LLM-based decision support system exists in the early and middle stages of product development where the technical problem is not yet fully defined and a wide variety of solutions may exist. The first challenge was one of practicality: a frozen baked good recipe named “Lemon Curd Poppy Seed Loaf” needed to be stable for a 6-month frozen storage time, but the current recipe and process did not provide enough stability. This is a problem that does not only depend on the recipe in product development practice. This includes the properties of raw materials, water state, enzymatic activity, proofing process, the impact of freezing and sensory acceptability.

The traditional approach to problem-solving is to make a hypothesis and run a production test or lab test, analyse the results, and modify the formula or process, repeating this cycle until the issue is resolved. Such approach is feasible but may take longer and cost more if it is not known what the most dominant quality mechanism is. This study assisted in reducing this time of uncertainty through the use of the LLM-DSS. The system not only suggested possible changes to ingredients or the process but also helped to link each scenario to a specific technological mechanism.

In the product development context, DSS undertook four important roles. It helped to set the problem in the right perspective. Rather than the generic conclusion that the product “did not meet shelf-life requirements”, the problem was associated with water migration, crumb structure stability, yeast activity and proofing conditions. Secondly, the DSS was used for the generation of several alternative solution paths: altering the recipe, adding water binding ingredients, altering the fermentation system and altering the process parameters. Thirdly, the system aided in reducing the set of solutions to two working experimental scenarios - S1 and S2.

The LLM-DSS is not a recipe generator but rather a tool to support decision making in the product development process. That is a significant difference. In food technology product development is not completely determined by recommendations from a generative model, but is limited by the specification of the ingredients, the presence of allergens, the customer requirements, the production equipment, the labelling and the food safety requirements. In this work, the principle of human-in-the-loop was applied for generation and justification of scenarios by the LLM and the final selection of the scenarios and validation of the results conducted by the human expert based on the technological logic, company requirements and experimental data [3, 4, 11].

In practical terms, the model is helpful for the R&D team, as it accelerates the process of moving from the problem to a testable solution. DSS does not do general or random testing but rather develops a test plan using causal logic. This is reflected in the two scenarios used in this study, namely S1 - water status and sensory softness, and S2 -fermentation system and proofing system. This also enabled the product to be compared as well as helped to understand which type of technological solution is the more beneficial.

From economic point of view, in the product development phase, this system can minimize the amount of tests that are not needed. In this paper, the initial decision space of six possible active directions was narrowed down to two experimental scenarios, a 66,7% reduction. Thus, the LLM-DSS could be used to narrow down production testing to the most likely hypotheses. Very specific benefits are available in an industrial bakery where each test requires raw materials, line time, manpower, energy and freezing capacity. If line capacity is 2400 units/hour, after only a couple of minutes of an unattractive production trial, time and resources costs can run high.

Table 33. The Role of LLM-DSS in the Product Development Phase

Product development stage	The traditional approach	The contribution of LLM-DSS to this study	Practical benefits
Problem statement	General description of the defect	The issue relates to water migration, structure, fermentation, and aging	A clearer technological hypothesis
Search for solutions	The technologist's experience and experiments	Several scientifically grounded approaches have been developed	A broader yet structured decision-making space
Scenario selection	Intuitive or limited selection	Select S1 and S2 based on mechanism, raw materials, and feasibility	Fewer unpromising attempts
Experimental validation	Testing and overall evaluation	Each scenario is linked to specific quality indicators	A clearer interpretation of the results
Deployment solution	Based on overall product improvement	Quality impact, cost, and process complexity are evaluated	A better management decision

As seen in Table 33, it illustrates that the LLM-DSS is not just used for coming up with technological ideas but has the potential to add value to the product development process. It is important for it to make a clear link between the problem, the hypothesis, the experiment and the solution. The structure is especially useful in the terms of this work that outlines not only the outcomes of the experiment, but also that the research was conducted in a consistent manner, and the methodology outlined in Chapter 2 was used throughout the work.

4.7. Social, Organizational and Managerial Impacts

The utilization of LLM-DSS not only has an economic dimension but also an organizational one in the product development stage. In food manufacturing companies, there are a lot of technological solutions that are based on experience of the technologists. This experience is very valuable, but not always well documented. This, in turn, can mean that the decision may rely on the experience of certain workers, their accessibility and their capacity to draw on a range of information quickly. The DSS model used in this study helps mitigate this risk, as the technological logic becomes more structured and transferable.

Socially this implies that the system can advance the company's knowledge administration system. If the product issue, possible scenarios, raw material constraints, experimental results and decision rationale are well documented in a single decision chain, then knowledge is not so reliant on individual memory. This is advantageous for new employees, the engineering staff, quality specialists, and managers. Product development no longer is a “trial and error” process, but a more logical, traceable and explainable decision-making process.

From a managerial viewpoint, LLM-DSS aids in better clarifying advantages and hazards in various scenarios. This study revealed that both S1 and S2 have a positive impact on product quality in their respective ways. S1 saw an increase in the cost of raw material of about 1,79 ct/unit but did not need to change the process which resulted in the best sensory outcome. S2 would have been more economical on raw materials (around 0,30 ct/unit) however, it would have needed an adjustment to the proofing regime, and it may have affected process capacity. Now it is possible to make a more concrete decision, one that is not based on abstract principles of "which product is better", but rather, one that deals with the question of whether the company wants to produce maximum sensory quality at a higher raw material cost, or alternatively, to produce a quality with a lower raw material cost, but with a higher requirement for process control. This difference is crucial for product development management.

The process flow remains unchanged in S1 making it more suitable for quick implementation. This will reduce operator error risk and make it easier to switch to production. S2 is better suited where the problem is more associated with structural unevenness or shape stability and should be used in conjunction with some extra process control - proofing temperature and duration, product dimensions and line rate.

LLM-DSS can also enhance communication between the R&D, manufacturing and quality control departments. One of the common practical issues is that the evaluations of the product are done differently by various departments. The objectives of R&D could be to improve texture, the production could be focused to ensure that the process and line are stable, the quality could be focused to ensure that the product meets the specifications and the commercial could be focused to ensure that the product is acceptable to customers. DSS can be used to integrate these into a single decision matrix. For this study, it is seen through an integrated evaluation - sensory evaluation, ImageJ results, raw material costs, and process impact was evaluated in conjunction.

It must be noted, however, that LLM-DSS does not take the place of human responsibility. Any recipe or process change in food production needs to be checked for food safety, allergen, label, customer and technological food stability. Thus, the system should be used as a decision support system and not as the decision maker. This is consistent with the human in the loop principle, which is especially crucial for the use of LLM in higher responsibility socio-technical systems [3, 4, 11].

4.8. The Environmental and Resource Use Importance in the Product Development Process

The environmental relevance of this research is primarily due to the possibility of minimizing unnecessary testing, defect and waste if better products development decisions are made. Every failed test is more than just a loss of raw material in the production of frozen baked goods. It also encompasses employee time, production line capacity, baking time, storage, proofing and mixing. Thus, indirect environmental benefits can exist with a DSS that can facilitate the rapid identification of scenarios that may prove positive.

In the case of this work, the environmental logic manifests itself on two levels. The initial step is the product development phase. The LLM-DSS narrowed the number of cases being tested from six to two cases, thus reducing the need for potentially unnecessary testing. Less raw materials will be used, and less production line capacity will be required for tests which would almost certainly be rejected. Product quality stability is the second level. The reduction in the potential amount of scrap and product rejection also occurs if S1 or S2 reduces the risk of quality defects after frozen storage. The area of the structural objects detected by S1 and S2 was reduced by the ImageJ analysis as compared to K0. The S1 %Area decreased by 42.8%, while S2 decreased by 56.4%. Both also showed to be more acceptable than the control in sensory analysis. This indicates that both solutions can help to minimize the likelihood of quality non-conformities. In this study, however, the actual reduction of waste was not measured, so the environmental conclusion should be drawn with caution: the results indicate the potential for waste reduction, but not a specific percentage of waste reduction.

Table 34. The Impact of LLM-DSS on Resource Utilization During Product Development and Manufacturing

Assessment level	Possible effects	The results of this study	Interpretation
Product development testing	Fewer unpromising attempts	A 66.7% reduction in active scenarios	Lower costs for raw materials, labour, and production time during the development phase
Raw materials	Additional or substituted raw materials	S1 +1.79 cents/unit; S2 +0.30 cents/unit	The S1 is more expensive, the S2 is cheaper, but both offer quality benefits
Process	Possible changes in process duration or energy consumption	S1 does not change the process; S2 may extend the proofing	S1 is simpler for resource management; S2 requires additional measurement
Consistency of quality	Lower risk of defects	S1 and S2 improved sensory and structural indicators	Potential for waste reduction
Decision-making	Faster and more accurate scenario selection	Clearly compare K0, S1, and S2	Less uncertainty in the development process

In the view of environment, the scenario S1 looks better as it has enhanced the quality without altering the process parameters. This is done mainly by formulation changes. Without changing the proofing process and without reducing line throughput. A disadvantage of this scenario is that it would be more expensive, and it requires extra ingredients. The overall resources management logic may be positive if this scenario contributes to the reduction of product rejections or customer complaints. For S2 the assessment is more complicated. It does not have any significant impact in terms of the raw materials as it only adds around 0,30 ct/unit to the cost price.

The lower proofing temperature and possibly as much as 5 minutes longer proofing time may impact the line's balance but not enough to cause any issues. Theoretical output could be reduced from 2400 to about 2250 units/hour if proofing is the limiting stage of the process. It implies, that the environmental and economic value of S2 should not only be measured for raw material, but also energy and actual capacity of the process.

The most important principle from an environmental point of view is that quality stability itself constitutes a conservation of resources. A product that remains structurally intact and acceptable after freezing is less likely to be a waste. This is especially true for products that are frozen, since they need the extra freezing and storage facilities. That makes it clear that quality stability is not just a commercial objective, but also a way to better utilize raw materials, energy and labour. Such strategy is in line with the literature on the use of AI and digital systems in food production, where it can be seen highlighted that data-driven decisions can lead to a reduction in waste, better use of resources, and better process control [43, 44, 45].

4.9. Chapter Summary

The value of LLM-DSS in this work is not only in the results of the product, but also in the product development process. It was showed by the social, economic and environmental assessment. The system was used to structure the quality problem, and by 66,7% decreased the search space for selected solutions and was able to identify two different scenarios verifiable in practice.

Economically, the best option for improving quality is S1. It improved the overall acceptability by 29,0%, the softness by 37,3% and the sensation of moisture by 37,9% while it raises the cost of raw materials by around 1,79 ct/unit or about 42,96 EUR/h for the line capacity of 2400 units/h. The cost of S2 is approximately 0,30 ct/unit or approximately 7,20 EUR/h lower with the raw materials, but the implementation is harder because it requires process adjustments and can have effects on the production capacity. S1 is the most appropriate initial implementation candidate from a product development point of view because it was the only option that showed improvements to the most significant sensory indicators without changing the process. S2 should be used as a target direction for further optimization if structural stability and crumb control are desired.

Environmentally, both scenarios could lower the number of defective products and waste, with both improving the structure and sensory quality indicators following frozen storage. Further production data will be needed to determine the actual effect on volume of waste, energy use, and production efficiency. Finally, it can be said that LLM-DSS may be a useful extension for product development and quality management in food production, if it is not utilized as a decision-maker but rather as a structured decision-support tool, which combines scientific literature, information on raw materials, process parameters, experimental results, and human expert judgment.

Conclusions

1. Based on the analysis of quality factors in recipe and technological process, it is possible to conclude that quality stability of the selected type of product is not associated with only a single ingredient but depends on the relationship between the recipe and technological process. For the studied product the key factors include the state of water, the sugar system, stability of the gluten network, enzyme activity, yeast activity, proofing technology and effects of freezing on crumb structure. It was concluded from practical considerations that quality problems in terms of frozen storage of the product involve alterations in softness, moisture level, structure of crumb, and general quality level. Thus, for improvement of quality, a comprehensive approach should be applied considering recipe and technological process.
2. The resulting LLM-DSS was capable of incorporating product formulations, technological parameters, limitations on raw materials, and quality characteristics into one optimized product model. Here LLM was not used as an autonomous decision-maker, but only as an additional tool for the development of various scenarios. Through the assistance of this model, the connection of the general problem and specific technological processes has been established. Decisions were filtered by human expert assessment, meaning that the designed DSS was based on the human-in-the-loop approach.
3. By implementing the proposed model into an industrial product, three experimental cases were tested, which permitted comparing different approaches for enhancing its quality. The initial scenario K0 was the existing control product. The second scenario S1 was built using the recipe modification strategy only. The purpose of this scenario was to stabilize the level of water and achieve better results in terms of maintaining softness and humidity. The third scenario S2 included recipe and process modifications. It meant that some flour was substituted with wheat malt, the amount of "CO2MMITTED BRIOCHE FREE 5%" improver was increased, and proofing temperature was lowered. Such structure allowed to evaluate not only individual changes but also compare which scenario is more suitable.
4. Experimental verification showed that both selected scenarios suggested by the LLM-DSS positively affected product quality after four months of frozen storage, although there were differences. Based on the sensory analysis, the overall acceptability score raised to 8,0 points in the scenario S1 from 6,2 points for the control sample K0 and to 7,7 points for S2. In terms of sensory quality, the scenario S1 most efficiently worked with softness and moisture perception. Therefore, S1 is recognized as a more effective way to improve the sensory quality indicator. Based on the ImageJ analysis, the area of identified structural objects was minimized for S1 and S2 compared to K0 - 42.8% for S1 and 56.4% for S2. Thus, S1 showed better results in the improvement of sensory qualities and the structure, whereas S2 showed better results regarding only structure.
5. Economic and managerial evaluation proved that the use of LLM-DSS could lead to increased efficiency of product development, decreased uncertainty of decisions made, and optimized usage of resources. The developed model helped to reduce the number of options to consider from six technological directions to only two experimental ones. This illustrates a chance to save in terms of testing, raw materials, labour, machine time, and analyses required for product development. Regarding economic issues, S1 was the best among all options considered in quality terms but rather costly one. The second option, S2, was less expensive, however, its realization requires a lot of effort and is likely to affect production capacity. Thus, taking into account economic aspects, S1 should be the preferred option, S2 should be used for process optimization purposes.

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Appendices

Appendix 1. Documentation on the Use of ChatGPT

ChatGPT was used as an LLM-based tool for generating and structuring DSS scenarios. The tool was provided with summarized product information: the recipe, the technological process, raw material constraints, specifications of the improvers used, and the quality issue. The tool was asked to generate possible scenarios for improving the quality stability of frozen yeast-leavened baked goods, distinguishing between recipe changes alone and combinations of recipe and process changes. The generated response proposed several approaches: adjustment of the sugar and water system, addition of inulin, optimization of the fermentation system, use of wheat malt, adjustment of the proofing temperature, and evaluation of freezing stability. The final scenarios used in this work were selected by the author based on data from the scientific literature, the company's raw material requirements, and the possibility of experimental verification [41].