UNIVERSITÀ DEGLI STUDI DELLA BASILICATA

University of Basilicata

Doctoral Course in
Agricultural, Forest and Food Sciences

Curriculum: Food Sciences and Engineering

SMART PLANT MANAGEMENT TO IMPROVE THE QUALITY AND SUSTAINABILITY OF BAKERY PRODUCTS

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XXXVII PhD Cycle

"When everything seems
to be going against you,
remember that
the airplane takes off
against the wind."

Contents

Summary

This doctoral thesis, *Smart plant management to improve the quality and sustainability of bakery products*, explores the integration of digital technologies and sustainable ingredient innovation in the bakery sector, with particular emphasis on gluten-free breadmaking. The work is framed within the evolving paradigm of Food Industry 5.0, which combines technological advancement with human-centricity, sustainability, and system resilience.

The first part of the thesis provides a critical review of the transition from Food Industry 4.0 to Food Industry 5.0, highlighting the role of enabling technologies such as the Internet of Things, automation, artificial intelligence, smart sensors, and data-driven decision support in modern agri-food systems. Special attention is given to the opportunities and challenges associated with digitalization in terms of efficiency, traceability, sustainability, and workforce involvement.

The second part presents an experimental study focused on the valorization of edible legume grains excluded from commercial markets due to aesthetic non-compliance, specifically through the production of dehulled bean flours derived from local *Fagioli di Sarconi* PGI ecotypes. Optimized pre-treatments were applied to improve dehulling efficiency, and the resulting flours were incorporated as partial substitutes in commercial gluten-free baking mixes. Breadmaking trials were conducted using a standardized recipe, and technological and physical quality attributes were systematically evaluated.

To support process optimization, a low-cost IoT-based monitoring system was developed using an ESP32 microcontroller and environmental sensors to track dough fermentation in real time. This approach enabled objective, continuous monitoring of leavening behavior and demonstrated the potential of smart, accessible technologies to improve process control in both research and small-scale bakery contexts.

Overall, the thesis demonstrates how the combined application of digital monitoring and circular raw-material valorization can contribute to improving the quality, sustainability, and resilience of gluten-free bakery products, offering practical tools and conceptual insights aligned with the principles of Food Industry 5.0.

Keywords

Food Industry 5.0; gluten-free bread; dehulled bean (*Phaseolus vulgaris L.*) flour; IoT-based monitoring; sustainable bakery; circular economy.

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Acknowledgements

This study was partially carried out within the project Pon “RESO – REsilienza e SOstenibilità delle filiere ortofrutticole e cerealicole per valorizzare i territori”, funded by the Italian Ministry of Education, Universities and Research (MIUR).

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From Food Industry 4.0 To Food Industry 5.0

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Introduction

Climate change, the growth in world population, high levels of food waste and food loss, and the risk of new disease or pandemic outbreaks are among the many challenges that threaten the sustainability of food systems and the food security of the planet (Hassoun, Aït-Kaddour *et al.*, 2023). Tackling these challenges—including global warming, pollution, biodiversity loss, deforestation for food production, the substantial amount of food waste and loss, the rapid increase in the global population, and the threat of future pandemics—requires the adoption of innovative, sustainable, and practical solutions in the agri-food sector to ensure sufficient food for all (Bahn *et al.*, 2021; Hassoun, Aït-Kaddour *et al.*, 2023; Senturk *et al.*, 2023). These pressures are prompting a critical rethinking of how food is produced, processed, and distributed across the supply chain. One dilemma is that while the food industry is already one of the most significant contributors to climate change, food production still needs to be increased to meet the growing demand of the rising population (Hassoun, Aït-Kaddour *et al.*, 2023). These complex challenges must be addressed in ways that minimize environmental degradation and promote equitable access to nutritious food as part of the broader effort to build sustainable food systems.

In this context, the Fourth Industrial Revolution (Industry 4.0 or 4IR), is already transforming many sectors, including the food industry. Recognized as a significant driver for sustainable development and an effective catalyst for addressing critical global challenges, it is characterized by the convergence of physical, digital, and biological technologies—such as Artificial Intelligence (AI), Machine Learning (ML), big data, cloud computing, the Internet of Things (IoT), blockchain, smart sensors, robotics, cybersecurity, digital twins, and cyber-physical systems (Maynard, 2015; Massabni & Da Silva, 2019; Bai *et al.*, 2020; Chapman *et al.*, 2021; Jagtap *et al.*, 2021; Jambrak *et al.*, 2021; Liu *et al.*, 2021; Hassoun, Aït-Kaddour *et al.*, 2023; Konur *et al.*, 2023).

Building on these developments, the global agri-food sector has entered a new phase marked by the convergence of smart technologies and evolving consumer demands. This technological transformation includes the implementation of digital technologies—such as AI, big data analytics, IoT, and blockchain—as well as other innovations like smart sensors, robotics and 3D food printing (Hasnan & Yusoff, 2018; Philbeck & Davis, 2018; Hassoun, Aït-Kaddour *et al.*, 2023; Alami *et al.*, 2024). AI is particularly transforming the food sector by optimizing processes, enhancing product quality and safety, and fostering innovation (Zatsu *et al.*, 2020). Robotic systems are revolutionizing food processing, enhancing both productivity and efficiency. The integration of these technologies is reshaping traditional food production and distribution systems, enhancing consistency and operational performance, and generating significant cost savings (Jideani *et al.*, 2020). The term “Food Industry 4.0” is often used to describe this digital evolution in the food sector (Hassoun, Jagtap *et* *al.*, 2023).

Over the past two decades, food systems have become increasingly complex and interconnected due to the interaction between demographic pressures, technological change, and new consumer expectations. These dynamics have led to greater automation, enhanced interconnectivity, and the widespread adoption of data-driven decision-making processes. Smart sensors and robotics are increasingly used across the food supply chain to optimize tasks in real time, while digital twins and CPS enable simulation, monitoring, and predictive control of food processes (Hassoun, Aït-Kaddour *et al.*, 2023). As a result, food systems have become more responsive and traceable, with improved ability to meet consumer demands and address operational challenges.

Industry 4.0 is characterized by rapid technological progress, primarily focused on internet-based systems, full automation, and the integration of digital tools. The digitalization of the food industry through the incorporation of big data analytics, smart sensors, autonomous robotics, and other advanced technologies has led to greater productivity, improved process stability, and the development of customizable products. These emerging digital technologies have significantly enhanced productivity and operational efficiency in the food industry (Hassoun, Aït-Kaddour *et al.*, 2023).

Industry 4.0 technologies have been adapted to meet the specific requirements of food systems, enabling applications such as intelligent food packaging, precision farming, and traceability systems (Hassoun, Aït-Kaddour *et al.*, 2023). This has led to what is often referred to as Food Industry 4.0: the application of digital and automation technologies across agriculture, processing, logistics, and food services, with the aim of enabling data-driven decision-making, improving food safety, and optimizing resource use.

In the food sector, these digital tools are being used to track products along the supply chain, monitor temperature fluctuations during storage and transport, and support targeted recalls of contaminated or defective goods without disrupting the rest of the system (Singh *et al.*, 2025). While Industry 4.0 has enabled the food industry to become more efficient, it has also raised concerns regarding energy consumption, job displacement, and the marginalization of small producers (Hassoun, Aït-Kaddour *et* *al.*, 2023). The heavy reliance on automation and cyber-physical systems raised concerns about job displacement, lack of adaptability, and the environmental impact of unchecked technological growth (Singh *et al.*, 2025).

However, the widespread adoption of Industry 4.0 has also exposed structural weaknesses. These emerging technologies have, on the one hand, allowed increased productivity and operational efficiency in the food industry, but on the other hand, they have led to some disruptions in the food supply chain and negative impacts on environmental sustainability (Hassoun, Aït-Kaddour *et al.*, 2023).

Issues such as automation-driven job displacement, high energy consumption, growing ethical issues, and data privacy risks have become increasingly evident. As a result, the era of Food Industry 4.0 has been characterized by both opportunities and emerging challenges, reshaping production and consumption models and laying the groundwork for the transition toward Industry 5.0 (Hassoun, Aït-Kaddour *et al.*, 2023). Furthermore, the techno-centric approach of Industry 4.0 may sometimes overlook the importance of human creativity and ethical considerations in technological applications, leading to social resistance and limited stakeholder acceptance (Hassoun *et al.*, 2024).

As the limitations of Industry 4.0 become more apparent, a new industrial paradigm—Industry 5.0—has emerged. Rather than replacing Industry 4.0, Industry 5.0 builds upon it, fostering a synergy between robotic precision and human creativity, and embedding ethical values into industrial processes. This model goes beyond technological efficiency by placing human-centricity, sustainability, and resilience at its core. Industry 5.0 offers a solution by shifting the focus from automation to human-machine collaboration (Singh *et al.*, 2025), redefining productivity and efficiency while addressing critical societal and environmental challenges.

This emerging paradigm represents a transition from prioritizing economic efficiency to generating broader societal value, placing human well-being and inclusivity at the core of industrial development (Singh *et al.*, 2025). Industry 5.0 proposes a more holistic, human-centric model, integrating advanced technologies with human creativity to support sustainable and resilient production systems that prioritize environmental and social well-being. It emphasizes interactions between humans and intelligent systems—such as collaborative robotics or Cobots—while promoting circular economy practices and adopting resilience-oriented strategies to foster environmental responsibility and strengthen food system responses to crises, including pandemics, armed conflicts, and climate change (Hassoun *et al.*, 2024). Cobots work alongside humans to enhance efficiency, safety, and adaptability in food production, supporting skilled professions, mass personalization, and inclusive, sustainable workplaces (Singh *et al.*, 2025).

This chapter provides an overview of the conceptual and technological shift from Food Industry 4.0, characterized by automation and data exchange, to Food Industry 5.0, which emphasizes human-centricity, sustainability, and resilience. It defines the core differences between the two paradigms, identifies the main technologies driving this transformation, and examines their impact on innovation, governance, and sustainable development in the food industry.

Overview of Industrial Revolutions in the Food Sector

Throughout history, mankind has experienced successive scientific revolutions that have reshaped the world, each characterized by transformative shifts in technology, ideas, and societal structures. These revolutions are ongoing, building upon one another to create a continuum of progress that spans decades. Their impacts are far-reaching, influencing various fields and aspects of life (Singh *et al.*, 2025).

The development of the global food sector has been deeply influenced by successive industrial revolutions, each marked by transformative technological innovations and shifts in production paradigms. From the mechanization of agriculture to the integration of artificial intelligence and smart automation, these revolutions have progressively redefined how food is produced, processed, distributed, and consumed.

The trajectory from Industry 1.0 to Industry 5.0 reflects an evolutionary path of technological convergence and societal adaptation (Figure 1.1).

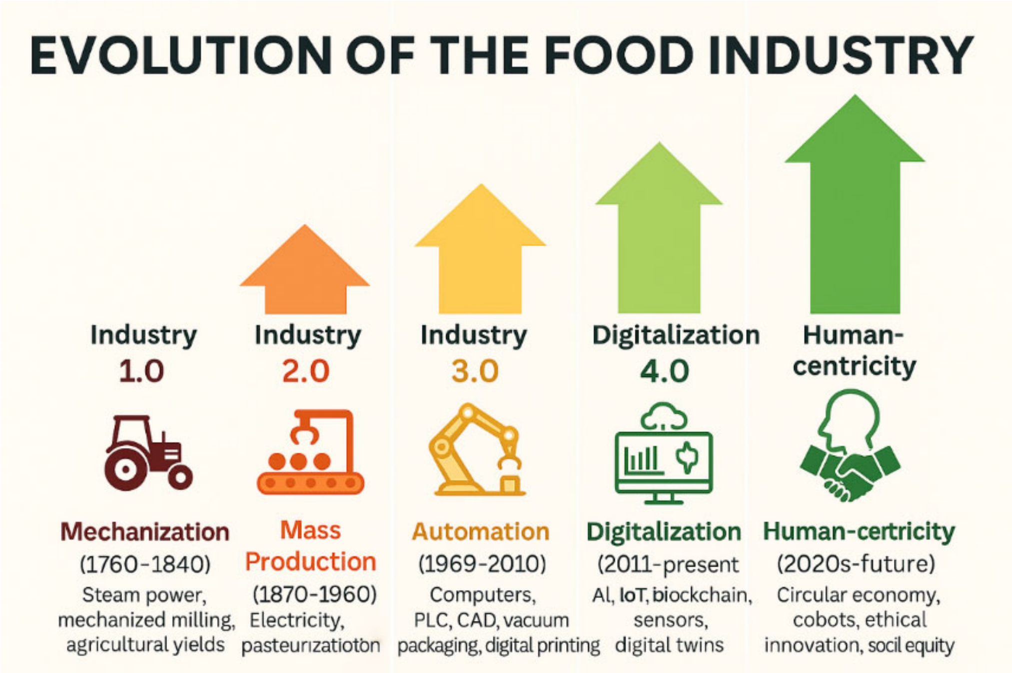

Figure 1.1. Key Features and Timelines of the Five Industrial Revolutions in the Food Sector. Each Stage Builds upon the Previous and Shifts the Priorities of Food Innovation (AI-Generated Image).

Industry 1.0 - Mechanization (1760-1840)

The First Industrial Revolution (1IR) began in the late 18th century and was characterized by the mechanization of manual labor and the introduction of mechanical power—through steam engines—which led to increased food production and agricultural yields. The use of steam power enabled mechanized milling, reduced the need for human labor, and improved preservation methods (Singh et al., 2025). The canning method, later adopted by many food industries for preservation, was also invented during this period (Jideani *et al.*, 2020).

Factories were reorganized to accommodate more workers and machines, boosting productivity (Hassoun, Aït-Kaddour *et al.*, 2023). The textile, coal, iron, and chemical sectors expanded significantly, alongside the shift of certain food products from household to factory-based manufacturing (Koetsier, 2019). Although the revolution was primarily driven by the textile and mining industries, these innovations substantially improved productivity in food processing and laid the foundation for large-scale food systems.

Industry 2.0 - Mass Production and Electrification (1870-1960)

The progression of mechanization led to the Second Industrial Revolution, characterized by the use of electricity instead of steam, which increased efficiency, expanded industrial capacity and enabled mass production. Innovations such as pasteurization and refrigeration improved food safety, extended shelf life, and enhanced distribution capabilities (Hassoun, Aït-Kaddour *et al.*, 2023; Singh *et al.*, 2025).

The electrification of factories enabled mechanized food processing, while assembly-line production increased the availability of processed foods. Among the food machinery introduced during this period were the first semi-automated extruders used to manufacture dry pasta and breakfast cereals; improved refrigerators equipped with cooling fans to prevent overheating during production; and ovens used in drying processes (Jideani *et al.*, 2020). These innovations collectively laid the foundation for the modern food industry (Singh *et al.*, 2025).

Industry 3.0 - Automation and Digital Electronics (1969-2010)

Known as the digital revolution, the Third Industrial Revolution marked a transition from analogue to digital systems. It was characterized by the introduction of computers, electronics, and information technology (IT), which enabled programmable control and early forms of digital monitoring in agriculture and food processing. These technological advances—particularly computers and the Internet—accelerated global communication and facilitated connections across production and distribution systems. In addition, production processes became increasingly automated through the adoption of electronic systems (Naboni & Paoletti, 2015; Hassoun, Aït-Kaddour *et al.*, 2023).

From a food industry perspective, this era witnessed the widespread adoption of the Chorleywood Bread Process, the use of digital printing on food packaging, and the introduction of vacuum packaging as a method of food preservation. Automation and digitalization enabled the implementation of process lines with programmable and automated machinery in the food sector.

One example is the automated and programmed bakery production line (Figure 1.2). These innovations significantly increased production efficiency, enhanced quality control and food safety, and enabled the development of novel food products (Singh *et al.*, 2025).

Figure 1.2. Automated and Programmable Bakery Process Line (Jideani *et al.*, 2020).

Industry 4.0 - Digitalization and Smart Technologies (2011-present)

The current Fourth Industrial Revolution (4IR) is based on the use of cyber-physical systems, automation, analytics, and the internet of things from the early 21st century (Allen, 2009) in the food and agro-processing industries. Industry 4.0 is characterized by the development of intelligent and interconnected machines and systems (Khan *et al.*, 2018). Key elements of Industry 4.0 include artificial intelligence, machine learning, smart sensors, big data, cyber-physical systems, the Internet of Things, robotics, digital twins, and blockchain (Hassoun, Aït-Kaddour *et al.*, 2023). These technologies have given rise to “smart factories” (Grabowska, 2020), increased productivity, and enhanced real-time monitoring in the food industry. AI is employed to develop machines capable of learning, particularly in food sensing applications that enhance safety and quality inspection. Automation and interconnectivity have improved efficiency and reduced food loss through better logistics and forecasting. Furthermore, Industry 4.0 has enabled applications such as blockchain for food traceability, digital twins for process optimization, and AI for personalized nutrition (Singh *et al.*, 2025).

Despite these advances, limitations emerged with Industry 4.0—particularly its techno-centric focus, high energy demands, and challenges in social equity and sustainability. Excessive automation raised concerns about labor displacement, while data governance and environmental impacts became central issues in both research and practice (Hassoun *et al.*, 2024). As a result, Industry 5.0 has emerged, focusing on human-machine collaboration and a more balanced approach that combines innovation with social and environmental responsibility (Singh *et al.*, 2025).

Industry 5.0 - Human-Centric, Sustainable, and Resilient Innovation (2020s-future)

Industry 5.0 introduces a shift from full automation to human-machine collaboration through cobots, placing greater emphasis on human creativity and empathy, as well as ethical values, resilience and sustainability. Its aim is to integrate technological innovation with environmental and social responsibility, prioritizing human well-being (Hassoun *et al.*, 2024; Singh *et al.*, 2025). This transition is supported by key enabling technologies such as AI, machine learning, IoT, blockchain, data analytics, and collaborative robots. These tools play a pivotal role in enhancing quality, efficiency, safety, and adaptability in food production and processing, while addressing the growing consumer demand for sustainable and ethical practices. Notable applications include waste reduction, smart labeling, and mass personalization (Singh *et al.*, 2025).

This emerging paradigm supports a shift toward more inclusive and regenerative food systems, where efficiency is not the sole objective, but rather part of a broader framework that values human and planetary health. Industry 5.0 aligns with the principles of the circular economy and the United Nations Sustainable Development Goals (SDGs), promoting localized, resilient, and socially responsible approaches to food production. Ultimately, it aims to enhance not only productivity and innovation, but also the well-being of workers, consumers, and the planet.

From Revolution to Evolution: A Continuum of Innovation in the Food Industry

The described five stages are not isolated revolutions but represent a continuum of innovation shaped by the socio-economic context and technological capabilities of each era. Like other sectors, the food industry has evolved in parallel with these broader industrial trends, progressively adopting new tools to enhance efficiency, quality, and scale.

During Industry 1.0, the introduction of steam-powered engines and mechanized milling revolutionized food processing, marking the first major shift from artisanal to factory-based food production.

Industry 2.0 further accelerated these transformations with the advent of electricity and assembly-line production. In the food sector, this led to advances in hygiene, refrigerated transport, and mass production of canned goods, significantly extending food availability and shelf life. Technologies like pasteurization and mechanized dairy production also emerged.

Industry 3.0—often referred to as the digital or information revolution—introduced programmable logic controllers (PLCs), electronics, and early computing systems (Pramanik *et al.*, 2019). These innovations enabled automation and quality control in food manufacturing, as well as new forms of packaging and labeling. Additionally, this era saw the rise of computer-aided design (CAD) and early simulation models, laying the groundwork for traceability and regulatory compliance.

Industry 4.0 built on these advancements by connecting machines, systems, and people through networked data platforms. Smart sensors, robotics, AI, and big data analytics allowed for real-time decision-making, predictive maintenance, personalized nutrition solutions, and automated food safety controls. Blockchain technologies have improved transparency in food supply chains, while 3D printing and non-thermal processing methods introduced new frontiers in food customization and quality preservation.

However, as digitalization deepened, so did its consequences. Excessive automation raised concerns about job displacement, data ownership, energy consumption, and social inequities in food access. These tensions gave rise to Industry

5.0, a new paradigm aiming to re-humanize the industrial process. The food sector is particularly well-suited to this shift, as it inherently intersects with health, environment, culture, and social equity.

Industry 5.0 thus proposes an integrated framework in which technology empowers human creativity, sustainability guides production, and resilience ensures continuity in the face of disruptions. This marks a significant transformation in the purpose and design of food systems—from efficiency-driven to value-driven innovation.

Understanding the trajectory of these five industrial revolutions is essential to contextualize the most recent transformations within the food sector. Among these stages, Industry 4.0 represents the pivotal technological foundation for the ongoing transition toward more sustainable, ethical, and resilient models. The following section will therefore focus on the definition, scope, technologies, and implications of Food Industry 4.0, to better understand how it sets the stage for the emergence of Food Industry 5.0.

Food Industry 4.0

Each industrial revolution has shaped the evolution of the food industry—from manual, localized practices to highly automated and globalized systems. Among these, Industry 4.0 has had the most profound and recent impact, introducing intelligent systems and data-driven processes across every stage of the agri-food value chain (Singh *et al.*, 2025). To fully understand the scope and implications of the transition toward Industry 5.0, it is first essential to define the context and features of Food Industry 4.0, which lays the technological and conceptual foundation for this shift.

Humanity is currently facing complex demographic, health, and nutritional crises that demand innovative and sustainable solutions (Galanakis, 2020). These include global warming and climate change, environmental pollution, biodiversity loss, deforestation driven by food production, widespread food loss and waste, rapid population growth, and the persistent threat of emerging diseases and pandemics

(Boyacı-Gündüz *et al.*, 2021; Mondejar *et al.*, 2021).

Although the food industry is already one of the main contributors to climate change, it must still increase production to meet growing global demand. As a result, food companies face unprecedented pressure to adopt sustainable technologies, foster innovation, and achieve high standards of performance (Chakka *et al.*, 2021; Chapman *et al.*, 2021). Within this context, the Fourth Industrial Revolution has gained traction across various sectors, including the food industry. Data from the Scopus database reveal a steady increase in academic interest in Food Industry 4.0 technologies—from one publication in 2020 to eight in 2024. Citation peaks in 2023 further highlight the impact of earlier studies, while lower 2024 citations reflect the recency of new research (Figure 1.3). This trend underscores growing recognition of the crucial role of Industry 4.0 technologies and digital innovation in advancing sustainable food systems. Furthermore, the COVID-19 pandemic acted as a catalyst, accelerating the digital transformation across the agri-food supply chain (Bakalis *et al.*, 2020; Amentae & Gebresenbet, 2021).

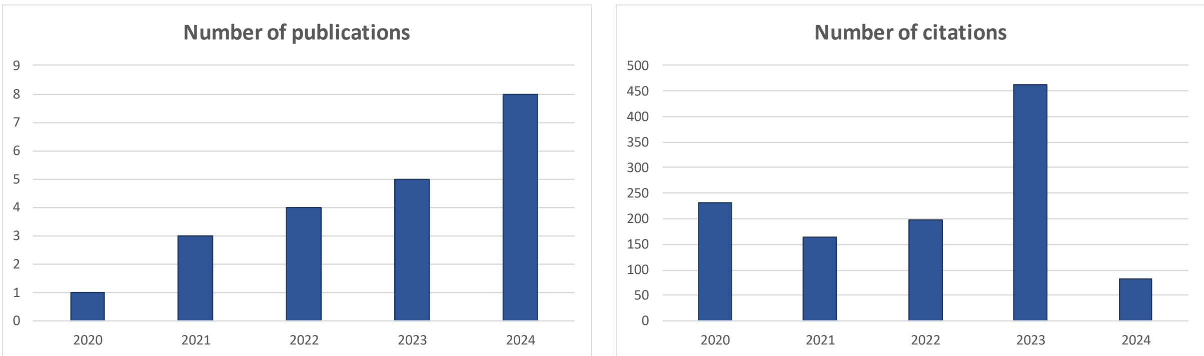

Figure 1.3. Publications (a) and Citations (b) Related to the 4IR in the Food Industry. Search Criteria: Food Industry 4.0 in Article Title, Abstract, Keywords.

From Innovation to Implementation: Challenges of Industry 4.0 in Food Systems

The main Industry 4.0 technologies, from a food perspective, include AI, ML, big data analytics, smart sensors and robotics, IoT, blockchain, digital twins and CPS, among others (Hassoun, Aït-Kaddour *et al.*, 2023).

AI has significantly improved food sensing technologies, contributing to safer, more standardized, and accountable food systems. AI and machine learning have accelerated the ability to forecast demand, detect anomalies in production, and even assess food quality via computer vision. These technologies are deeply intertwined with big data analytics, which allow companies to derive insights from vast datasets collected by sensors and user interactions across the food value chain (Hassoun, Aït-Kaddour *et al.*, 2023).

Smart sensors are now widely deployed throughout the entire food value chain (Mayer & Baeumner, 2019) for food safety, nutritional quality assessment, traceability, and real-time process monitoring. Spectroscopy-based sensors, for instance, are applied to optimize enzymatic protein hydrolysis of various industrial by-products into high-value products (Wubset *et al.*, 2019) and are combined with chemometric tools to authenticate food products through their spectral fingerprint (Hassoun *et al.*, 2020; Valand *et al.*, 2020). Alongside optical technologies, electrochemical sensors are integrated in-line during processing for food safety and quality monitoring (Mayer & Baeumner, 2019; Ivanišević *et al.*, 2021), or embedded into smart packaging to detect changes in temperature, humidity, oxygen, pH, and chemical composition, or microbial contamination (Yousefi *et al.*, 2019; Rodrigues *et al.*, 2021; Shao *et al.*, 2021; Cheng *et al.*, 2022).

Industrial robots can reduce production time and costs in the food industry (Bader & Rahimifard 2020; Duong *et al.* 2020). However, their adoption remains limited due to stringent safety and hygiene standards, high investment costs, and the complexity of handling non-uniform food products (Iqbal *et al.*, 2017; Jagtap *et al.* 2021). Currently, robots are most commonly used in end-of-line processes such as packaging and palletizing (Iqbal *et al.*, 2017), where the material is more uniform.

IoT devices have been used in combination with RFID to track and trace food across a range of applications, including food safety and quality monitoring, shelf life and pesticide residue detection, traceability, and anti-counterfeiting. However, several challenges persist. The most critical is the lack of infrastructure to support the connectivity required for seamless data collection and analysis. High implementation costs and concerns over network security also pose significant barriers (Bouzembrak *et al.*, 2019; Jagtap *et al.*, 2021).

Blockchain technology can offer a solution to the lack of traceability and trackability in traditional food supply chains by connecting and tracking data from producer to consumer. This enables more accurate and faster recalls and helps reduce food losses along the global supply chain (Kayikci *et al.*, 2020; Javaid *et al.* 2021). Several studies have explored the integration of blockchain with other emerging technologies to enhance food traceability and supply chain transparency. For example, blockchain has been combined with IoT and HACCP (Hazard Analysis and Critical Control Points) systems for real-time food tracing (Tian, 2017); with IoT for autonomous monitoring of perishable goods during transport (Bhutta & Ahmad, 2021); and with both IoT and deep learning to verify the origin of agricultural products (Khan *et al.*, 2020). Despite its potential, blockchain adoption in the food industry remains limited, as most applications are still in early pilot stages. Key barriers include high implementation costs, a lack of technical skills and training, and unresolved challenges related to regulation, data privacy, storage capacity, and latency (Zhao *et al.*, 2019; Kamilaris *et al.*, 2019; Khan *et al.*, 2020; Jagtap *et al.*, 2021).

Digital twin technology, integrated with IoT and AI, enables the synchronization of physical activities with the virtual world. These models can be statistical, data-driven, or physics-based (Tao *et al.*, 2019; Verboven *et al.*, 2020; Defraeye *et al.*, 2021; Burg *et al.*, 2021). Although still in early stages within the food industry (Verboven *et al.*, 2020; Burg *et al.*, 2021), some promising applications have emerged. For instance, digital fruit twins have been developed to simulate the thermal behavior of mangoes along the cold chain, improving refrigeration processes and logistics for a more sustainable supply chain (Defraeye *et al.*, 2019).

Cyber-Physical Systems integrate the physical and virtual worlds through a global network infrastructure and share some key principles with digital twins. While their application in the food and agricultural sectors remains limited, CPS hold great potential for enabling smart factories. However, challenges such as system complexity, lack of technical standards, and cybersecurity concerns still need to be addressed (Iqbal *et al.*, 2017; Lu, 2017).

Although many emerging technologies remain at the experimental stage, several Industry 4.0 solutions have already been successfully implemented across different sectors of the food industry to optimize production, enhance quality assurance, and improve supply chain transparency (Singh *et al.*, 2025).

In food processing, Process Analytical Technology (PAT), Advanced Process Control (APC), Model-Predictive Control (MPC), and Statistical Process Control (SPC) are used to monitor and control key quality attributes to improve efficiency and reduce waste, with AI and ML playing critical roles in these advancements (Mengistu & Ashe, 2024; Yang *et al.*, 2025). These technologies are successfully applied to optimize production processes and improve product quality, while similar approaches support equipment monitoring for predictive maintenance (Dalzochio *et al.*, 2020). Collectively, they enable more precise process control and greater operational reliability (Singh *et al.*, 2025).

Innovation and new product development drive competitiveness in the food industry, with AI significantly reducing R&D costs and improving success rates. Techniques such as social media text mining help identify consumer needs and generate product ideas (Patroni *et al.*, 2020; Zhang *et al.*, 2021), while hybrid modeling—combining machine learning and mechanical models—optimizes formulations for sensory quality and shelf life. These advancements enhance innovation and efficiency in product development (Kuhl, 2025).

AI and ML have emerged as powerful tools in the domain of food safety. AI has the potential to transform how food-related risks are detected, monitored, and predicted. By leveraging large volumes of data—from sensors, images, and spectral analyses—AI models can learn to distinguish between safe and unsafe food in real time (Karanth *et al.*, 2023; Liu *et al.*, 2023; Chhetri, 2024). An AI-powered food safety system can streamline food safety workflows by integrating data ingestion and predictive analytics, enabling proactive and scalable interventions (Kakani *et al.*, 2020; Balakrishnan *et al.*, 2025).

Finally, emerging technologies such as IoT, AI, big data, blockchain, nanobiotechnology, smart sensors, and 3D printing offer innovative solutions for optimizing smart packaging and reducing food waste. IoT devices and sensors enable real-time monitoring of food storage conditions and freshness, while AI analyzes this data to predict consumption trends, helping producers minimize waste. Big data contributes to improving packaging designs based on consumer preferences, and blockchain ensures traceability across the supply chain. Additionally, 3D printing enhances packaging customization, while nanobiotechnology transforms food waste into valuable materials for smart packaging applications (Hassoun, Boukid *et al.*, 2023).

Despite its transformative potential, the implementation of Food Industry 4.0 remains uneven, exposing several structural limitations that have drawn increasing criticism from researchers and stakeholders. While its technology-centric approach can optimize production and enhance supply chain transparency, it often overlooks critical aspects such as human well-being, social equity, and ecological sustainability (Hassoun, Aït-Kaddour *et al.*, 2023; Hassoun *et al.*, 2024). In particular, the focus on automation and efficiency has contributed to workforce displacement—especially in low-skill roles—raising concerns about job security and social exclusion. Moreover, high capital investment, limited technical expertise, and interoperability issues continue to hinder adoption—particularly among small and medium-sized enterprises (SMEs).

Environmental concerns have also emerged, as the high energy demand of always-on devices and cloud infrastructure, along with the lifecycle emissions of smart equipment, can undermine the very sustainability goals that digitalization promised to achieve. In addition, cybersecurity risks—including data breaches to operational sabotage—pose serious threats to food integrity and consumer trust (Hassoun *et al.*, 2024). Therefore, while Food Industry 4.0 provides powerful tools to modernize food systems, it also introduces new vulnerabilities that must be addressed through thoughtful design, regulatory oversight, and inclusive innovation policies.

These unresolved limitations highlight the need for a paradigm shift—one that builds upon the achievements of Industry 4.0 while addressing its systemic gaps. This has led to the emergence of Food Industry 5.0, a new approach that seeks to re-center the role of humans, promote environmental responsibility, and enhance systemic resilience in the face of global uncertainties. Rather than abandoning the digital foundations of the previous era, Industry 5.0 aspires to harmonize technological advancement with ethical values and social purpose, offering a vision for the future of food that is not only smarter, but also more sustainable and human-centric.

Overall, while Industry 4.0 has introduced transformative capabilities to the food sector, its uneven adoption and emerging drawbacks necessitate a more inclusive, sustainable, and human-centered model—setting the stage for the Food Industry 5.0 era.

The Emergence of Food Industry 5.0

While Industry 4.0 was driven by productivity, automation, and datafication, the Fifth Industrial Revolution (5IR) rebalances this progress by embedding human-centric values, sustainability, and resilience at its core (Hassoun, Aït-Kaddour *et al.*, 2023). This is especially significant in the food sector, where consumer trust, environmental constraints, and labor dynamics demand more inclusive and responsible innovation.

Industry 4.0 has primarily focused on technological advancements in the industrial landscape, often neglecting societal and human aspects (Table 1.1). The widespread deployment of autonomous technologies has raised concerns about job displacement and social inequality, highlighting the urgency of transitioning toward more socioeconomically balanced models (Nahavandi, 2019; Hassoun, 2024).

In response to these challenges, Food Industry 5.0 has emerged not as a rejection of Industry 4.0, but as a human-centered evolution that reorients its technological advancements toward ethical, inclusive, and sustainable objectives. It redefines the role of technology—not as a substitute for human labor and creativity, but as a technological partner that augments human decision-making and aligns with broader societal needs (Hassoun, Aït-Kaddour *et al.*, 2023).

This vision emphasizes how digital systems amplify human creative problem-solving to foster inclusive innovation. It also prompts the need to address new ethical, organizational, and regulatory challenges—including the redesign of workspaces, training needs, and the legal classification of intelligent machines (Demir *et al.*, 2019).

Food Industry 4.0 focused predominantly on automation and digitalization, creating highly efficient yet often impersonal production ecosystems. While these systems optimized productivity, they also introduced critical challenges: job displacement, cybersecurity vulnerabilities, social disengagement, and increased environmental pressures.

In contrast, Industry 5.0 repositions humans at the center—not as passive operators of automated systems but as creative collaborators. Rather than pursuing full automation, it promotes "cobotic" collaboration, in which collaborative robots (Cobots) work side by side with humans, enhancing dexterity, ergonomics, and decision-making.

Table 1.1. Key Differences between Food Industry 4.0 and Food Industry 5.0.

Dimension	Food Industry 4.0	Food Industry 5.0
Focus	· Automation, · Efficiency · Data-driven optimization	· Human-centricity · Sustainability · Resilience
Main Technologies	· AI · IoT · Big Data · Blockchain · CPS · Robotics · Digital Twins	· Regenerative AI · Cobots · Edge Computing · IoE · 6G · Metaverse · Nanosensors
Role of Humans	Minimized through automation	Reintegrated as co-creators and decision-makers (human-machine collaboration)
Sustainability	Indirect; often secondary to productivity goals	Central principle; circular economy and eco-efficiency embedded
Production Model	Smart factories; centralized digital control	Symbiotic systems; decentralized and adaptable platforms
Job Impact	Risk of displacement and deskilling	Focus on job transformation, inclusion, and upskilling
System Design	Techno-centric and top-down	Holistic, participatory, and interdisciplinary
Cybersecurity & Ethics	Emerging concern; often underdeveloped frameworks	Integral to design: emphasis on trust, transparency, and ethical AI
Resource Use	Optimized through data analytics and automation	Minimized through bio-based systems and real-time circular feedback
Resilience to Disruption	Limited, often fragile under shocks	Designed for adaptive capacity and predictive response to crises

An illustrative concept within this transition is "Industrial Upcycling", which emphasizes the shared use of tools like industrial robots and 3D printers in cooperation with human operators, rather than replacing them. This approach advocates for increasing human productivity and fostering more sustainable and intelligent collaboration (Coelho *et al.*, 2023).

Interest in Industry 5.0 has grown rapidly in academic and scientific domains in recent years, as evidenced by the sharp increase in related publications between 2016 and 2024 in the Scopus Database (Figure 1.4). This surge points to a growing recognition of the need for technological innovation that supports broader social and environmental objectives (Hassoun *et al.*, 2024).

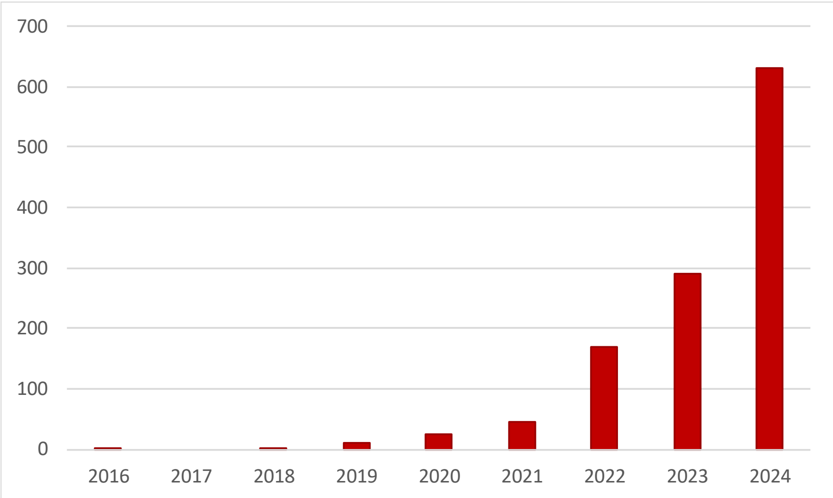

Figure 1.4. Evolution of the Number of Publications on Industry 5.0 from 2016 to 2024. Source: Data Obtained from the Scopus Database Using the Search Query: "Industry 5.0" OR "Fifth Industrial Revolution" in Article Title, Abstract, or Keywords.

As illustrated, the number of publications remained minimal until around 2019, but rose sharply after 2020—likely driven by global disruptions such as the COVID-19 pandemic. The acceleration of academic output reveals increasing awareness of the vulnerabilities of hyper-automated supply chains and the need for more resilient, adaptive, and ethically governed systems—highlighting the rising relevance of Industry 5.0 and its transformative potential within food systems.

Current research efforts are actively defining the goals, methodologies, and boundaries of Industry 5.0 as a new stage of industrial development. Unlike previous paradigms focused solely on efficiency, this emerging model seeks to address global societal and environmental challenges through disruptive technologies and inclusive innovation frameworks.

Industry 4.0 and Industry 5.0 represent two distinct but interconnected stages in the evolution of technological and industrial innovation. Industry 4.0 focuses primarily on automation, digitalization, and data-driven efficiency through the deployment of CPS, IoT, AI, cloud computing, and blockchain—alongside robotics, smart sensors, and drones—with the goal of building "smart factories" featuring interconnected systems that optimize productivity and cost-effectiveness through real-time decision-making (Singh *et al.*, 2025).

Industry 5.0 builds on this legacy of its predecessor by embracing a more holistic, participatory and ethically grounded model of innovation. It seeks to integrate advanced technologies with human creativity, ethical awareness, and environmental responsibility, aiming for a resilient and sustainable industrial future. In this context, smart factories facilitate seamless interactions between workers and intelligent machines to enhance flexibility and responsiveness. (Singh *et al.*, 2025).

Potential enabling technologies for Industry 5.0 include advanced AI, the Internet of Everything (IoE), cobots, next-generation drones, nanosensors, 4D printing, edge computing, redactable blockchain, immersive interfaces, and sixth-generation wireless (6G), among others (Xu *et al.*, 2021; Huang *et al.*, 2022; Mourtzis *et al.*, 2022; Tallat *et al.*, 2024;).

While Industry 4.0 has predominantly been driven by profit and centered on technological advancement, Industry 5.0 emphasizes a more balanced approach—between automation and human ingenuity, productivity and sustainability, and innovation and inclusivity. This shift is particularly relevant for the food sector, which requires not only operational efficiency but also social trust, safety, and ecological integrity.

Although numerous studies have explored the applications of Industry 5.0 across various fields (Javaid *et al.*, 2020; Frederico, 2021; Gürdür *et al.*, 2022; Jafari *et al.*, 2022; Marinelli, 2023), research focused on the agri-food sector remains limited. The concept of "Food Industry 5.0" has only recently entered the scientific literature, representing an emerging field with considerable potential for innovation and systemic transformation.

Core Principles of Food Industry 5.0

The concept of Industry 5.0 was first introduced during the CeBIT 2017 trade fair in Hannover, Germany (Shiroishi *et al*., 2018), as a continuation and evolution of the Industry 4.0 paradigm. Building on the digital foundations of its predecessor, Industry 5.0 represents a substantial shift toward greater human involvement and collaboration with intelligent systems (Mourtzis *et al*., 2022).

The Food 4.0 approach marked a turning point by enhancing interconnectivity among machines, devices, humans, and sensors (Martindale *et al*., 2022). However, despite these advancements, several limitations have emerged. High initial investment costs and a shortage of skilled labor have led to an overreliance on automation, resulting in job displacement. Moreover, the continuous operation of interconnected infrastructures raises sustainability concerns due to increased energy consumption, while the widespread use of IoT and big data technologies heightens the risk of cyber-attacks and unauthorized data access. The pursuit of efficiency and productivity has also exacerbated environmental degradation due to the reliance on non-renewable resources and increased waste generation. Additionally, the strong technological focus has sometimes neglected the importance of ethical considerations and human creativity, resulting in social resistance and a lack of stakeholder engagement.

Figure 1.5. Core Pillars of Food Industry 5.0: Human-Centricity, Sustainability, and Resilience. These Principles Guide the Integration of Advanced Technologies with Ethical, Social, and Environmental Priorities to Build Future-Proof Food Systems (AI-Generated Image).

In response to these challenges, the Food 5.0 approach has emerged—not as a rejection of previous developments, but as an evolutionary step that reinforces the integration of digital technologies with broader social goals (Elangovan, 2021; Tallat *et al.*, 2024). At the core of this vision lie three fundamental pillars: a human-centric focus on well-being and skill development, sustainability through the 3Rs—reduce, reuse, and recycle, and resilience in the face to disruption (Figure 1.5) (Ivanov, 2023). Food Industry 5.0 thus envisions a future in which technological progress is leveraged to generate inclusive social and economic value, ensuring that innovation advances not only efficiency, but also human well-being and active participation.

From Automation to Augmentation: The Role of Humans

In the realm of Food 4.0, the primary focus was on deploying technologies aimed at optimizing food production processes, leading to the implementation of automated systems that significantly accelerated and streamlined operations. However, this technological progress often came at the expense of human labor, with machines replacing tasks previously performed by workers (Martindale *et al.*, 2022).

In contrast, Food 5.0 marks a shift from automation to human augmentation—placing people back at the center of innovation and redefining their role not as operators but as empowered collaborators within smart systems. The goal is to promote human-machine collaboration, in which technology no longer aims to replace human labor, but acts as a partner in decision-making and skill enhancement (Tallat *et al.*, 2024). This paradigm shift has fostered the development of innovative solutions that enhance, rather than supplant, human involvement across various industries.

Cobots exemplify this approach, as they are designed to operate safely alongside humans in shared tasks such as packaging, quality inspection, and ingredient handling (Singh *et al.*, 2025). They support ergonomic workflows and foster adaptability in dynamic production environments. A practical example can be seen in the bakery sector, where collaborative robots work alongside humans to perform tasks such as traying up bagels and placing them on trolleys, while operators retain oversight and perform higher-level decisions (El Zaatari *et al.*, 2019). Moreover, augmented reality (AR) is increasingly being used in industrial settings, offering step-by-step visual guidance to support maintenance or inspection tasks by overlaying digital instructions onto physical environments (Jagtap *et al.*, 2021; Singh *et al.*, 2025).

The overarching objective of Food 5.0 is to establish a symbiotic relationship between humans and machines—one in which each complements the strengths of the other. This cooperative model fosters not only technological progress but also human growth and creativity, envisioning a future in which both entities thrive through mutual enhancement.

Sustainability as a Core Value

Industry 4.0 contributed to improvements in resource efficiency and waste reduction, but its primary focus remained on productivity and automation. In contrast, Industry 5.0 places sustainability at the heart of technological development, embedding ecological, ethical, and social considerations into the design and deployment of innovation (Hassoun *et al.*, 2024). It marks a transformative shift in the food sector by bridging advanced computational technologies with human ingenuity to build systems that are not only more efficient, but also environmentally sustainable and highly personalized (Singh *et al.*, 2025).

A defining feature of Food 5.0 is its commitment to fostering a sustainable food system that minimizes carbon emissions and environmental impact. To achieve this, the sector is embracing circular economy principles across the entire agri-food chain. Technologies are no longer deployed solely for maximizing productivity, but for their ability to reduce resource consumption, repurpose by-products, and extract value from waste and energy streams (Sikder *et al.*, 2023).

Within this paradigm, the focus extends beyond waste reduction toward valorizing unavoidable waste. When waste cannot be prevented, it is transformed into resources such as ingredients for human consumption, animal feed, fertilizer, or energy. These practices not only reduce the environmental footprint of food production but also support a regenerative approach to resource management.

Given the food industry's substantial reliance on water and energy resources, optimizing resource use represents a major opportunity to enhance sustainability and resilience. By limiting dependence on fossil fuels and reducing greenhouse gas emissions, these innovations contribute to the decarbonization of food systems while promoting long-term environmental health.

Governments and regulatory bodies worldwide are accelerating this transition through targeted policies and incentive frameworks that encourage lower emissions, circular practices, and responsible decision-making throughout the food supply chain. These collaborative efforts reflect a global commitment to aligning food innovation with the SDGs, and foundational values of Industry 5.0.

Ultimately, sustainability in Food Industry 5.0 is no longer an optional goal but a central metric of success. Technologies are valued not only for their output, but by how they produce it, and for whom—marking a critical evolution toward a more ethical, circular, and future-oriented food system.

Resilience at the Heart of Food Industry 5.0

Resilience—the capacity to absorb shock, adapt to change, and recover from adversity—has become a strategic necessity in today's food systems (Williams *et al.*, 2017). Recent and ongoing geopolitical crises, including the Russia-Ukraine conflict, the war in Gaza, and the long-term effects of the COVID-19 pandemic, have highlighted the profound vulnerability of global food supply chains to such shocks (Agrawal *et al.*, 2024; Hassoun *et al.*, 2024; Jagtap *et al.*, 2022; Mahroof *et al.*, 2024). In addition to geopolitical instability, climate-related disasters such as floods, droughts, and earthquakes have further revealed structural fragilities in food systems, leading to widespread shortages of food and labor (Jagtap *et al.*, 2024). These events underscore the urgent need for more robust and adaptable food systems.

In this context, digital tools, including IoT, big data analytics, and real-time monitoring technologies offer new opportunities to enhance visibility, anticipate disruptions, and enable rapid response. Such tools can play a pivotal role in strengthening supply chain agility and minimizing downtime during crises (Misra *et al.*, 2020).

Building resilience is no longer a reactive strategy—it is a proactive investment in food security. Leveraging digital innovation allows the food industry to better manage uncertainty, protect critical infrastructures, and ensure a continuous supply of safe, nutritious food even under extreme conditions. Ultimately, in a world marked by volatility and uncertainty, making resilience a foundational principle of food systems is not optional but imperative for safeguarding public well-being, economic stability, and long-term sustainability (Singh *et al.*, 2025).

Key Enabling Technologies of Industry 5.0

The foundational technologies of Industry 5.0 achieve their full potential only when integrated into broader systems and technological frameworks. It is the synergistic combination of these components within unified architectures that enables Industry 5.0 to fully realize its transformative capabilities.

Big data analytics and artificial intelligence

Big data analytics and AI are driving a profound transformation in the food industry, playing a pivotal role across key areas such as quality control, production optimization, supply chain management, product customization, sustainability, food safety, consumer behavior analysis, and research and development. These technologies enable the analysis of complex datasets, reveal hidden patterns and automate tasks traditionally performed by humans.

In quality control, solutions like AgShift's Hydra-AI combine 3D vision and cloud systems to detect imperfections in products such as raspberries, strawberries, and almonds, with high precision and without human bias (Stoitsis *et al.*, 2023). Companies like Nestlé and McCormick & Company leverage AI for product innovation and customization—developing Dalgona coffee and plant-based probiotic supplements based on data trends, or creating tailored spice blends that align with market demand and reduce product development time (Misra *et al.*, 2020).

AI also supports predictive maintenance, as shown by Nestlé's use of AI to minimize downtime and enhance operational efficiency. Moreover, IBM's platforms, including Food Trust® and the Sterling® Control Tower, improve supply chain performance by ensuring transparency, traceability, regulatory compliance, fraud prevention, and sustainability. Together, these applications demonstrates the wide-ranging impact of AI and big data analytics in advancing personalization, process optimization, and consumer engagement across the food sector.

Digital twins (DT)

Digital Twins enable automated real-time analysis of processes across interconnected machines and data sources, facilitating faster identification and correction of errors. Moreover, they offer significant efficiency gains and cost savings in industrial manufacturing, demonstrating their growing relevance and value in the context of Industry 5.0 (Lv, 2023). In the food industry, digital twins involve the creation of virtual replicas of physical processes, equipment, and products, with the aim of improving operational efficiency, product quality, and environmental sustainability (Attaran & Celik, 2023; Lv, 2023).

In practice, digital twins are applied across multiple domains within the food sector. Siemens' Food and Beverage Digital Twin solution, for example, integrates real-time data into virtual models to optimize production lines and energy consumption (Burčiar & Važan, 2022). Nestlé employs digital twins technology for quality control, using real-time sensor data to monitor and ensure consistency in the taste and texture of chocolate products (Das & Dey, 2021). IBM's Food Trust system applies blockchain-based digital twins to improve transparency and traceability across the supply chain, providing an immutable record of transactions and addressing concerns related to food safety and fraud (Suhail *et al.*, 2022).

The Digital Twin Core employs predictive models and optimization algorithms to simulate physical systems, integrating both real-time and historical data through an interactive interface. The "Historian" module manages historical datasets, while communication interfaces link IoT devices with external platforms such as supply chain systems.

Ultimately, digital twin technologies are revolutionizing the food industry by enabling data-driven decision-making, optimizing production, and accelerating innovation while maintaining high standards of quality and sustainability.

Internet of Things (IoT)

In Industry 5.0, sensor devices at the physical layer collect data from a variety of applications and transmit it to network and application layers for further processing. This data is then converted into actionable insights. In production environments, IoT-enabled sensors and automated machinery streamline operations by enabling real-time monitoring and control. Such monitoring is crucial to ensure optimal equipment performance, enhance productivity, and maintain safety standards in food processing operations (Singh *et al.*, 2025).

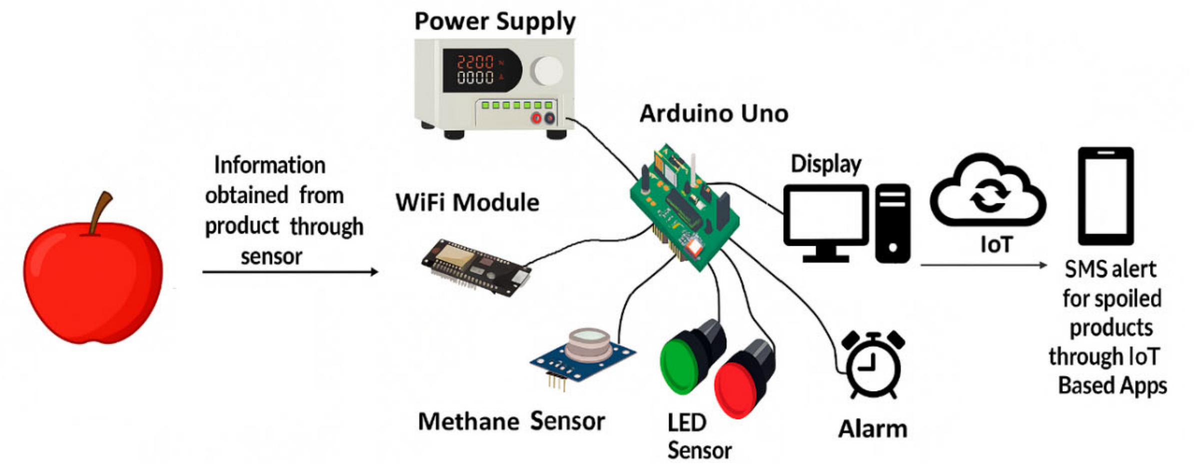

Figure 1.6. IoT Based Food Spoilage Detection System Using Arduino Uno (Dadhaneeya *et al.*, 2023).

Figure 1.6 illustrates an IoT-based food spoilage detection system that employs Arduino Uno, methane sensor, and IoT applications to monitor environmental conditions associated with spoilage. This system provides real-time alerts, thereby enhancing food safety and contributing to waste reduction during storage and transportation (Singh *et al.*, 2025).

In manufacturing and processing environments, IoT enables the real-time monitoring of critical equipment such as ovens, mixers, dryers, and conveyors (Dadhaneeya *et al.*, 2023). This continuous supervision ensures precise control of key operational parameters—such as temperature during baking—leading to improved product consistency and overall process optimization.

In the food industry, IoT technologies play a key role in quality analysis, smart packaging, and supply chain management. Sensors can monitor parameters such as pH in dairy processing, while smart packaging equipped with embedded sensors provides consumers with real-time freshness data (Dadhaneeya *et al.*, 2023). QR codes on seafood packaging, for instance, allow full traceability from catch to consumption (Putra & Labasariyani, 2023). More broadly, IoT has proven effective in monitoring quality, freshness, shelf-life, processing conditions, and authenticity across various products—including mushrooms, fish, meat, cheese, grains, sugar, coffee, beer, and other beverages. These applications highlight IoT's transformative potential in enhancing food safety, transparency, and sustainability.

The Internet of Everything (IoE) expands on the capabilities of IoT by connecting not only devices but also people, data, and processes (Hassoun *et al.*, 2024). In the food industry, IoE enables the seamless collection and transmission of data to optimize operations, ensure product quality, enhance traceability, reduce waste, and support sustainability goals.

Edge and Fog Computing

Unlike traditional cloud computing, edge computing processes data directly at the network's edge. This proximity to production lines enables faster decision-making, reduces latency, and improves operational efficiency.

In the food industry, it supports key Industry 5.0 objectives by allowing real-time monitoring of production, storage, and transportation, via IoT sensors and gateways. This localized data processing ensures rapid response to anomalies, optimizes resource use, maintains product quality, and strengthens both system resilience and data security. Typical applications include equipment diagnostics, quality assurance, and food safety control (Pham *et al.*, 2020).

Edge computing plays a crucial role in predictive maintenance and sustainability by enabling real-time data processing directly at the source. For example, in the gummy candy industry, a camera-equipped conveyor and a deep learning system detect defective candies, triggering their automated removal via blowguns. This system, with user-friendly monitoring features, enables direct product inspections and machinery management (Chen *et al.*, 2022).

Fog computing, operating with limited computing, storage, and networking capabilities distributed across end devices, supports latency-sensitive IoT applications, distinguishing it from traditional cloud computing (Atlam *et al.*, 2018). In food traceability, fog computing integrates cyber-physical systems and enterprise architectures (e.g., value stream mapping, EPC global), enabling collaborative and efficient traceable streams through both distributed and centralized mechanisms (Chen, 2017).

Collaborative Robots (Cobots)

Cobots are specifically designed to work safely alongside humans, enhancing their capabilities and making automation more accessible—even for small enterprises. In the context of Industry 5.0, cobots play a central role in fostering human-robot collaboration and ensuring greater flexibility in production. In the food industry, they contribute to improving efficiency, safety, and adaptability by assisting with tasks such as packaging, quality inspection, and ingredient handling.

Equipped with sensors, manipulator arms, and real-time data processing, cobots are capable of performing delicate operations with precision. Advanced features like AI integration and collision detection systems ensure safe interaction with human operators, reducing errors and boosting productivity. By enabling a dynamic and responsive production environment, cobots help maintain high standards of quality while adapting to evolving industry needs (Simões *et al.*, 2020; Sahan *et al.*, 2023).

Blockchain

Blockchain technology plays a crucial role in addressing the complexity of managing interconnected devices in Industry 5.0 by providing decentralized and distributed platforms that establish trust without the need for intermediaries. In the food sector, blockchain enables the secure and tamper-proof recording of data related to sourcing, production, and handling—enhancing traceability, improving food safety, and minimizing fraud and inefficiencies. Through end-to-end transparency, blockchain allows stakeholders to trace food products from farm to fork, as demonstrated by Walmart's use case in tracking the origin of mangoes (Wang *et al.*, 2023). This rapid traceability is especially valuable in responding to safety incidents and improving consumer trust.

Moreover, smart contracts automate processes such as quality control and inventory management, contributing to greater efficiency and a reduction in food waste, thus supporting sustainability goals (Kamath, 2018). Blockchain's compartmentalized architecture further reinforces data integrity and transaction security (Da Xu *et al.*, 2021), aligning with the Industry 5.0 principles of transparency, collaboration, and resilience across the entire supply chain (Bafti *et al.*, 2023).

Internet of Everything (IoE)

The Internet of Everything (IoE) builds upon IoT by interconnecting people, processes, data, and things into a unified network (Hassoun *et al.*, 2024). In the context of Industry 5.0, IoE plays a pivotal role in the food industry by promoting human-machine collaboration and enabling real-time, data-driven decision-making.

By connecting devices, sensors, and systems throughout the food supply chain, IoE facilitates seamless data exchange that enhances process optimization, quality control, and resource efficiency. It improves traceability by monitoring products from farm to table, supports continuous monitoring of production conditions through smart sensors. These capabilities contribute to greater sustainability, food safety, and operational transparency, aligning with the human-centric and resilient vision of Industry 5.0 (Yang *et al.*, 2022; Wu *et al.*, 2023).

6G

The integration of 6G technologies into Industry 5.0 marks a major leap forward, enabling ultra-low latency, high data throughput, and seamless integration of IoT infrastructure with advanced AI capabilities. These next-generation networks enable intelligent spectrum allocation, real-time edge computing, and enhanced mobility solutions—laying the groundwork for more agile and responsive industrial systems (Singh *et al.*, 2025).

In the food sector, 6G enhances supply chain operations, enabling advanced applications that improve performance, transparency, and resource efficiency. By delivering unparalleled data speeds, reliability, and energy optimization, 6G supports end-to-end connectivity across all stages of the food value chain—from precision agriculture using IoT and drones, to automated processing, dynamic logistics, and real-time consumer engagement. This high-capacity network infrastructure empowers smarter decision-making and boosts operational resilience throughout the food system (Padhi & Charrua-Santos, 2021).

Extended/Augmented reality

Extended Reality (XR)—which encompasses Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR)—is emerging as a powerful enabler of human-machine interaction in the food sector. These immersive technologies are particularly relevant to the goals of Industry 5.0, offering innovative ways to enhance operational workflows. In particular, AR applications have demonstrated strong potential in optimizing maintenance processes by improving task precision, reducing execution time, minimizing operational risks, and lowering costs through predictive insights and preventative interventions (Todorović *et al.*, 2019).

Integration of Industry 5.0 in Food Processing

In the food sector, Industry 5.0 tackles challenges by fostering collaboration between humans and machines. This approach integrates advanced technologies such as IoT for real-time monitoring, robotics for optimizing production workflows, and blockchain to ensure traceability and transparency throughout the supply chain. Cobots and smart manufacturing systems contribute to improved operational efficiency, while digital twin models allow for process simulation and product personalization. To address critical issues like connectivity and cybersecurity, Industry 5.0 also incorporates blockchain and edge computing technologies, leading to a more responsive, secure, and streamlined production ecosystem (Antonucci *et al.*, 2019; Tao *et al.*, 2014).

In the dairy industry, key challenges such as supply chain inefficiencies, quality control, and traceability gaps can be effectively addressed through the integration of

Industry 5.0 technologies. The use of smart sensors, IoT, blockchain, and AI enables more efficient, transparent, and sustainable operations. This digital transformation supports intelligent production systems that not only optimize processes but also reduce environmental impact (Luna *et al.*, 2016; Malik *et al.*, 2024).

In the cereal industry, Industry 5.0 enables agile and responsive production through smart manufacturing, IoT, AI, and advanced data analytics. Sensor-integrated machinery enhances real-time monitoring, blockchain ensures supply chain transparency, and AI-driven quality control improves product consistency, collectively optimizing efficiency and overall quality (Panda *et al.*, 2023).

In the fruit and vegetable industry, Industry 5.0 drives transformation through automation, robotics, IoT, and data analytics. These technologies boost productivity, reduce labor costs, and enable real-time crop monitoring to optimize yields and quality. Precision agriculture enhances resource efficiency and sustainability, while blockchain and machine vision systems improve quality control and traceability. Smart packaging and shelf-life extension solutions reduce waste and improve storage. Fruit-picking robots reduce manual errors, and the integration of digital tools ensures transparent, efficient, and sustainable supply chains (Wang *et al.*, 2022; Yap *et al.*, 2024).

In the tea and coffee industry, the integration of IoT, AI, and blockchain enhances traceability and ensures product authenticity and quality. Smart sensors and data analytics optimize production processes, improving efficiency and consistency (Singh *et al.*, 2025).

Finally, Industry 5.0 is transforming the beverage industry by integrating automation, robotics, IoT, AI, data analytics, blockchain, and sustainability strategies. These technologies enable streamlined manufacturing, real-time monitoring, product personalization, and improved traceability, while reducing environmental impact. For example, IoT sensors and AI algorithms enhance fermentation by maintaining ideal conditions and ensuring consistent product quality. Additionally, smart supply chain systems minimize waste and improve logistics, boosting overall efficiency in beverage production (Singh *et al.*, 2025).

Challenges and Future Directions

The successful implementation of Industry 5.0 in the food sector entails complex challenges spanning organizational, technological, economic, regulatory, and operational domains. Organizationally, limited engagement from senior management and a widespread shortage of skilled personnel hinder progress. Overcoming these barriers requires a cultural shift supported by awareness initiatives and stronger collaboration with educational institutions to reskill the workforce. As Hassoun *et al.* (2024) point out, the future food workforce must combine competencies in food science, engineering, computer science, and ethics. However, current training systems are not yet adequately aligned with this interdisciplinary convergence, contributing to a growing skills gap.

From a technological perspective, integrating heterogeneous data sources—such as sensors, supply chain databases, and consumer analytics—requires standardized protocols, secure digital architectures, and shared ethical principles. The lack of agreement on data ownership, access rights, and the responsible use of AI creates uncertainty, discouraging investment and slowing innovation. Effective data governance and interoperability frameworks are critical to ensure transparency, accountability, and trust in increasingly automated decision-making processes.

Economically, high implementation costs and the lingering financial impact of the COVID-19 pandemic represent major hurdles, particularly SMEs. Many of these businesses struggle to invest in advanced digital systems. To address this, greater support is needed through scalable, low-cost technologies—such as open-source platforms and mobile IoT devices—as well as through government-backed subsidies and shared infrastructure programs that make innovation more accessible.

Regulatory and ethical challenges also persist. The absence of clear legal frameworks and growing concerns about privacy, cybersecurity, and the role of automation call for transparent policies that balance innovation with social responsibility. Regulatory clarity is essential for managing emerging issues such as intelligent machine accountability, ethical AI deployment, and labor protection in human-robot collaboration.

Operational difficulties, including insufficient internet infrastructure, device compatibility issues, and the complexity of integrating diverse technologies into legacy systems, further complicate adoption. These barriers can be mitigated by promoting modular implementation strategies and scalable digital infrastructures adapted to the specific maturity level of different actors within the food supply chain.

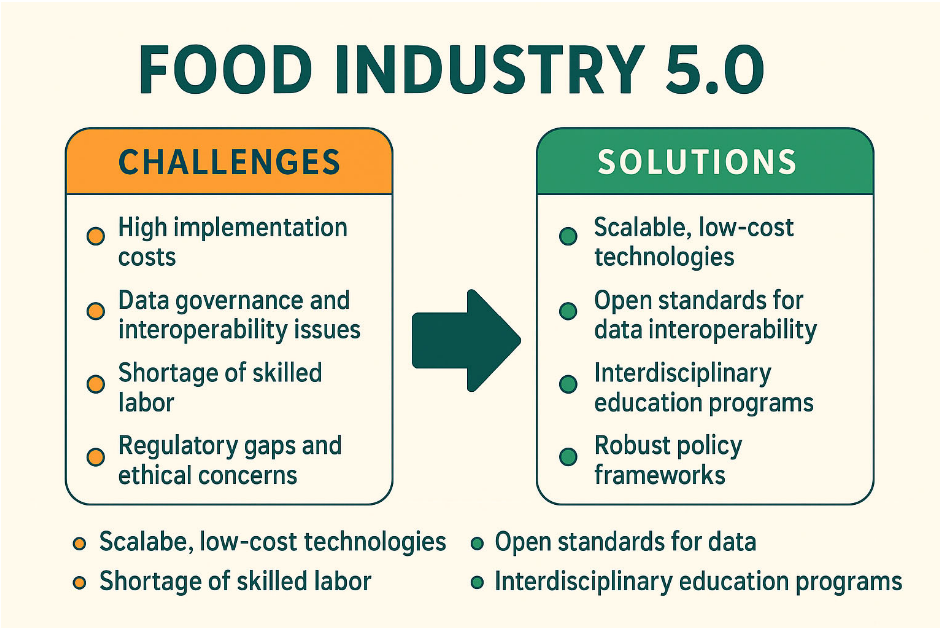

Figure 1.7. Key challenges and solutions for the implementation of Food Industry 5.0 (AI-Generated Image).

Addressing these interconnected challenges demands a unified and strategic approach. Future policy and research efforts must focus on developing affordable technology pathways for under-resourced actors, establishing open and interoperable standards, and promoting interdisciplinary education and training. Building an inclusive, transparent, and resilient Food Industry 5.0 will ultimately depend on collaborative action between governments, academic institutions, and industry stakeholders. Such cooperation is crucial to ensure that innovation is not only technologically advanced but also ethical, sustainable, and aligned with shared societal goals.

Conclusion

The transition toward Food Industry 5.0 signifies a strategic and necessary redefinition of how food systems are conceived, operated, and governed. Moving beyond the efficiency-driven logic of Industry 4.0, this new paradigm promotes a more holistic model that places human values, environmental stewardship, and technological innovation on equal footing. By fostering synergistic collaboration between advanced technologies—such as AI, IoT, blockchain, digital twins, and 6G—and human expertise, Food Industry 5.0 enables the creation of a more adaptive, transparent, and sustainable food ecosystem.

However, the path to implementation is not without challenges. Economic constraints, regulatory uncertainties, data governance complexities, and skills shortages remain significant barriers. Overcoming these will require coordinated efforts among industry stakeholders, governments, and academic institutions, along with investments in scalable technologies, interdisciplinary education, and inclusive policy frameworks.

Ultimately, Food Industry 5.0 offers more than technological advancement; it proposes a new way of thinking about food production and consumption—one that is resilient, ethical, and aligned with global sustainability goals. By embedding human and planetary priorities at the core of innovation, this emerging model holds the transformative potential to reshape the future of food systems, ensuring resilience, ethics, and long-term sustainability.

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Digital Transformation In the Bakery Sector

2

From Industry 4.0 Tools to Industry 5.0 Needs

Introduction

As a vital segment of the global food sector, the bakery industry—which has traditionally relied on artisanship, manual processes, and traditional techniques—is undergoing a significant transformation driven by Industry 4.0 and digitalization (Melesse & Orrù, 2025). Technological innovations such as automation and robotics, blockchain, Wireless Sensor Networks (WSNs), and other digital platforms are redefining how bakery products are developed, produced, monitored, and delivered.

The advancements introduced by the Industry 4.0 paradigm, in terms of digitalization and automation, have brought substantial benefits, including increased efficiency, improved product quality and safety, enhanced traceability and transparency, waste reduction, and better responsiveness to evolving market demands (Dabic-Miletic, 2023; Konfo *et al.*, 2023; Panigraphi *et al.*, 2025).

However, as the sector continues to evolve, so do its priorities. Beyond efficiency and automation, the food system increasingly demands sustainability, personalization, and human-centric solutions (Adel, 2022; Singh *et al.*, 2025). This shift aligns with the principles of Industry 5.0, which emphasizes the synergy between advanced technologies and human creativity, while promoting resilience, environmental responsibility, and social value (Dixson-Declève *et al*, 2022; Singh *et al.*, 2025; Vahdanjoo *et al.*, 2025). In this context, the bakery sector represents fertile ground for observing and enabling a smooth transition between these two industrial paradigms (Figure 2.1).

Figure 2.1. From Industry 4.0 to Industry 5.0: Efficiency to Human-Centric Innovation (AI-Generated Image).

Digitalization is already revolutionizing bakery operations—from real-time process monitoring to smart supply chain management, quality control, and enhanced customer engagement (Bordel *et al.*, 2021; Melesse & Orrù, 2025). However, the integration of such technologies faces several challenges, especially in traditional or small-scale bakeries, due to high initial investment costs, issues related to digital literacy, and concerns about the loss of their artisanal quality (Rohan & Benjamin, 2024; Melesse & Orrù, 2025).

This chapter explores the current state of digital transformation in the bakery sector, examining the key technological innovations, analyzing their benefits and challenges, and outlining the emerging needs that call for a more inclusive and sustainable technological integration—particularly within small- and medium-sized enterprises (SMEs) and artisanal bakeries.

Technological Innovations in the Bakery Sector

The bakery industry must adopt advanced digital solutions to enhance automation and optimize supply chain processes in order to maintain competitiveness in an increasingly dynamic market (Zaitsev, 2023). A 2022 survey revealed that approximately 46% of bakery sector stakeholders were inclined to invest in new machinery and innovative products, while around 32% considered investing in automation. These advancements can significantly improve operational efficiency and data-driven decision-making, help navigate supply chain disruptions, reduce human error, and align with evolving customer expectations. In parallel, digital transformation is reshaping sales behaviors, prompting bakeries to embrace e-commerce and online platforms to expand market reach and strengthen customer engagement (Melesse & Orrù, 2025).

Digitalization involves the integration of a wide array of technologies—including AI, big data, smart sensors, IoT, blockchain, robotics, digital twins, and virtual and augmented reality—designed to mitigate the impact of global health crises and environmental challenges on food systems (Hassoun, Marvin *et al.*, 2023). In the bakery industry, these technologies are applied to enhance product quality, reduce waste, and automate production lines. Specifically, they enable remote technical support, automated inventory replenishment, predictive maintenance, and continuous quality control (Bordel *et al.*, 2021).

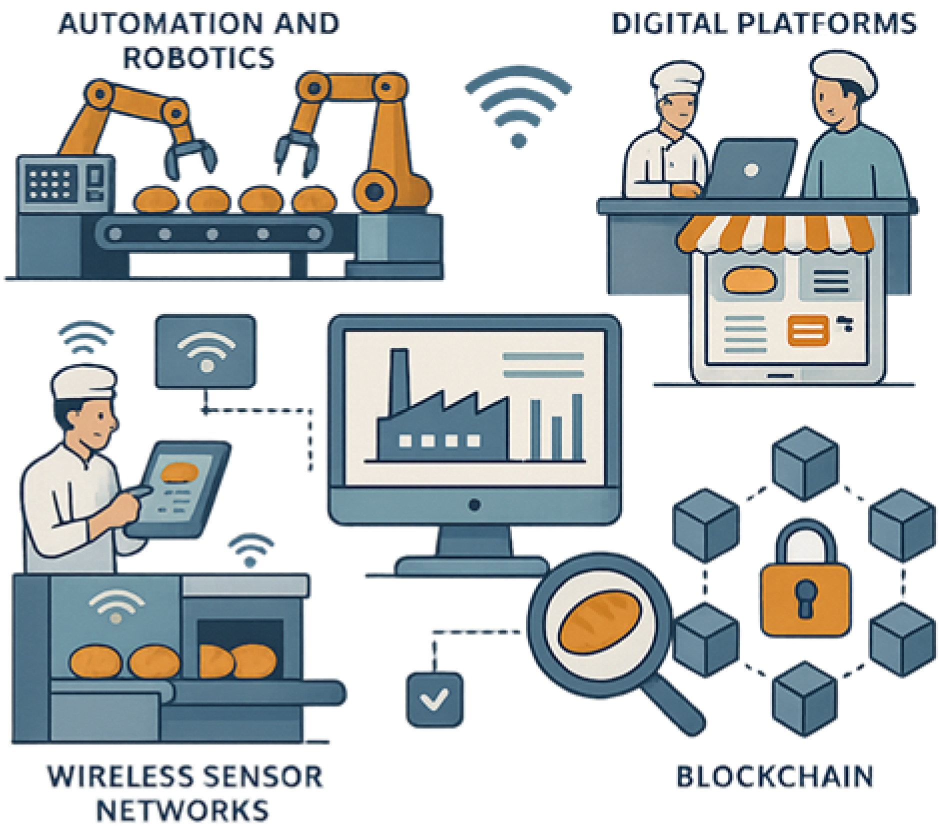

Figure 2.2. Key Technological Innovation Identified in the Bakery Industry (AI-Generated Image).

Smart technologies also allow for real-time production monitoring, demand forecasting, and interactive customer communication via digital platforms. Furthermore, they strengthen traceability and transparency throughout the supply chain, supporting compliance with food safety regulations and addressing sustainability-related consumer concerns. Overall, the integration of digital technologies and platforms is reshaping bakery operations, enhancing not only efficiency and productivity but also adaptability and product quality (Melesse & Orrù, 2025).

Automation and Robotics

Automation and robotics are playing an increasingly strategic role in the modern bakery sector by optimizing production processes, ensuring consistent product quality, and reducing physical labor. These technologies are applied across various stages of the production chain—such as dough mixing, fermentation, and baking—resulting in enhanced operational efficiency, improved quality control, strengthened food safety, and greater product traceability (Quintana *et al.*, 2012; Baire *et al.*, 2019; Logeswaran *et al.*, 2022; Aghababaei *et al.*, 2025).

According to the Food Engineering's State of Food Manufacturing Survey, automation in bakery processing lines can boost productivity by 10–15% (Melesse & Orrù, 2025). Technological upgrades not only increase throughput but also enhance worker safety and reduce labor costs. Innovative solutions—such as ergonomic design, wearable monitoring devices, and virtual reality training—are being explored to support workforce adaptation to digital workflows (Quintana *et al.*, 2012).

Robotic systems are increasingly deployed to handle repetitive or physically demanding tasks, allowing human workers to focus on higher-value operations (Grohmann *et al.*, 2022; Logeswaran *et al.*, 2022). Despite technical barriers such as process variability and high computational demands, robotics continues to gain traction as a promising strategy to address labor shortages and improve manufacturing productivity (Logeswaran *et al.*, 2022).

Currently, automation in bakery sales is being explored to reduce labor demands and accelerate customer service. For instance, Faster R-CNN-based point-of-sale (POS) modules are being implemented to expedite the order encoding process, thereby increasing retail store productivity (Yeung *et al.*, 2023). Similarly, convolutional neural networks (CNNs) are used to monitor physical transformations in bread during baking—tracking changes in texture and color resulting from moisture loss, as well as Maillard and caramelization reactions (da Silva Cotrim *et al.*, 2020). In addition, machine learning (ML) models have been applied to automate data segmentation and analysis, providing deeper insight into the porous structure of bread dough and streamlining experimental workflows. Bread quality evaluation has also been enhanced through the integration of shape and volume metrics with deep learning techniques, particularly the YOLOv5 algorithm (Ali *et al.*, 2021; Rohan Joel *et al.*, 2024).

Automation has also been applied to traditional products like Pane Carasau, using microwave and dielectric spectroscopy to monitor dough properties and leavening through models such as the third-order Cole–Cole equation (Lodi *et al.*, 2021; Maccio *et al.*, 2023). Additionally, automated systems combining machine learning, super ellipsoid fitting, and laser sensors have been developed to track dough volume and fermentation in real time (Giefer *et al.*, 2019). These technologies improve process control, reduce waste, and enhance production efficiency, even in artisanal contexts (Melesse & Orrù, 2025).

While automation presents clear advantages, it also requires substantial initial investment costs, higher energy consumption, and an increasing reliance on technically skilled labor. For SMEs, its feasibility of automation must be carefully evaluated in light of available financing, market demands, and production scales. Moreover, transitioning human operators into collaborative roles with machines, and ensuring the adaptability of robotic systems to product variability, remain unresolved challenges (Derossi *et al.*, 2023; Hassoun, Jagtap *et al.*, 2023; Wakchaure *et al.*, 2023; Baek *et al.*, 2024).

Blockchain

Blockchain technology enables secure, transparent, immutable, and integrity-protected data management, making it particularly suitable for ensuring traceability and fostering consumer trust across food supply chains—effectively bridging the farm-to-table gap. In the bakery industry, it can be applied to track the journey of raw materials, allowing consumers to verify the origin and quality of products and access detailed product histories (Melesse & Orrù, 2025). For instance, a blockchain-based system was proposed for managing the supply chain of Pane Carasau, integrating Radio Frequency Identification (RFID), Near Field Communication (NFC), smartphones, and IoT technologies to address data quality gaps and improve traceability during bread production (Cocco *et al.*, 2021; Yeung *et al.*, 2023).

However, technical challenges remain. Public blockchains like Ethereum and Bitcoin suffer from high latency and slow transaction speeds due to proof-of-work (PoW) protocols, limiting their use in real-time bakery supply chains. Private blockchains such as Hyperledger Fabric offer better performance and lower energy consumption, but reduce decentralization and may introduce security concerns

(Melesse & Orrù, 2025).

Additional obstacles arise from the lack of direct compatibility between blockchain platforms and bakery management systems such as Enterprise Resource Planning (ERP) software and IoT infrastructures, often requiring middleware solutions that increase complexity and costs. Moreover, blockchain's immutability can hinder compliance with the General Data Protection Regulation (GDPR) and food safety regulation, as it complicates data modification. Although off-chain storage offers a workaround, it comes at the expense of reduced transparency (Melesse & Orrù, 2025).

Wireless Sensor Networks (WSNs)

The adoption of WSNs and IoT technologies is transforming traditional bakery operations by enabling real-time monitoring, predictive maintenance, and process optimization (Melis et al., 2020). WSNs have been effectively applied to monitor bread-baking processes. For instance, pilot-scale electric ovens have used digital images and filler temperature data to control heating and belt speed, thereby improving product consistency (Pereira *et al.*, 2016).

In the case of Pane Carasau, WSNs have proven useful for collecting real-time data and optimizing production in small-scale bakeries through low-cost electronics and user-friendly interfaces (Baire *et al.*, 2019; Melis *et al.*, 2020; Baire *et al.*, 2021; Lodi *et al.*, 2021). Image segmentation methods using machine learning (ML) techniques have been applied to ensure quality control through accurate segmentation and estimation (Mannaro *et al.*, 2022). ML-based object detection models have also been developed to identify, classify, and count baked goods, helping bakers track unsold products, optimize production, and improve resource use. Additionally, a model-based PID controller has been implemented in online proofing monitoring systems to measure dough volume, compensate for yeast-related variations, and reduce manual intervention—thus enhancing productivity and product quality (Melesse & Orrù, 2025).

Despite their advantages, WSNs face several technical challenges. Battery-powered sensors require frequent replacement, while energy-harvesting alternatives often lack stability. Communication protocols such as Wi-Fi and Zigbee are susceptible to interference from bakery equipment, whereas more reliable options like 5G or wired networks entail significantly higher costs. Sensor drift—a gradual change in sensor accuracy over time—can also compromise food quality. Furthermore, security remains a key concern, as encryption and blockchain technologies improve data protection but introduce additional computational demands and system complexity (Melesse & Orrù, 2025).

Digital Platforms

Digital platforms are transforming the bakery sector by connecting stakeholders, streaming operations, and improving supply chain efficiency. They enable services such as online food delivery, inventory management, and reservations, while accelerating time to market for new products (Marra, 2022).

Traditional bakeries are adopting these tools to promote products, expand e-commerce, and engage customers via social media. Examples include the DIGIFOOD dashboard, which monitors local and online bakery markets, compares outlet performance, and identifies underserved areas (Jia et al., 2024), and "ArteBianca Delivery" in Southern Italy, which leveraged digital platforms to enhance marketing, delivery, and customer care (Barile *et al.*, 2024). In Hungary, digital tools have supported consumer preference studies through the Food Choice Questionnaire (Biró & Gere, 2021). Digitalization further supports environmental sustainability by enabling machine-readable Environmental Product Declarations and automating Life Cycle Assessment (LCA) data management, thus improving benchmarking, statistical analysis, and error detection (Melesse & Orrù, 2025).

However, challenges remain. Barriers include, especially for SMEs, high implementation and maintenance costs, integration challenges with existing equipment, and the need for staff training, which may face resistance (Agostini & Nosella, 2020). Data security, scalability limits, and reduced customer interaction are further concerns, alongside the environmental footprint of cloud-based services (Melesse & Orrù, 2025).

Benefits of Digitalization in the Bakery Industry

The integration of digital technologies in the bakery sector delivers benefits across operational, economic, and consumer-oriented dimensions. Digitalization modernizes production by enabling automation, data-driven decision-making, quality control, and traceability (Tian, 2016; Cocco *et al.*, 2021; Mannaro *et al.*, 2022; Agrawal *et al.*, 2025).

Automation and robotics streamline routine tasks—such as dough mixing and baking—resulting in higher throughput, fewer human errors, and improved worker safety (Quintana *et al.*, 2012). Real-time monitoring through sensors and smart controllers allows precise regulation of environmental and process variables, optimizing resource use and minimizing energy consumption (Tian, 2016).

Technologies such as blockchain, IoT, and WSNs provide end-to-end traceability from raw material sourcing to final product delivery. These tools support regulatory compliance, enhance transparency, and enable rapid response to food safety incidents (Morchid *et al.*, 2024). For example, blockchain systems combined with RFID/NFC technologies have been used in traditional bakeries to trace the production and distribution of Pane Carasau, ensuring product authenticity and reinforcing consumer trust (Cocco *et al.*, 2021; Kaur *et al.*, 2024).

Smart sensors and machine learning models enable continuous product quality monitoring, detecting deviations in texture, browning, volume, or moisture at early stages. These systems can significantly reduce waste, particularly in processes with tight quality tolerances such as fermentation and baking (Kaur *et al.*, 2024). Microwave and dielectric spectroscopy have also proven effective for optimizing leavening and fermentation stages, reducing trial-and-error in traditional formulations (Lodi *et al.*, 2021). Automated classification tools for browning and crust quality help further support consistency, especially in large-scale production (Castro *et al.*, 2017).

Digitalization also supports informed decision-making in recipe formulation, inventory management, and energy optimization (Aijaz, 2025). Furthermore, digitized Life Cycle Assessment (LCA) systems contribute to environmental transparency, enabling bakeries to benchmark ecological performance and improve resource management through automation and system integration (Welling & Ryding, 2021).

Challenges and Barriers to Implementation

Despite its clear advantages, the adoption of digitalization in the bakery sector—especially among SMEs and artisan producers—faces significant economic, technical, and cultural barriers. High implementation costs for automation equipment, sensor networks, software platforms, and cybersecurity infrastructure remain one of the main obstacles. For small bakeries, achieving a return on investment often requires an extended time frame, making such investments difficult to justify in the short term. Moreover, digital systems demand ongoing maintenance, regular updates, and technical support, further increasing long-term costs (Zavodna *et al.*, 2024).

A lack of digital literacy among bakery owners and staff is another constraint, particularly in family-run or artisanal settings (Giefer *et al.*, 2019; Grohmann *et al.*, 2022). The absence of training programs and dedicated personnel hampers effective adoption, while cultural resistance persists among those who fear that automation could diminish craftsmanship or the perceived authenticity of their products (da Rocha *et al.*, 2023).

Integrating digital tools into existing operations also presents technical challenges. Legacy machines and manual processes may be incompatible with modern sensors, cloud-based dashboards, or blockchain platforms, often requiring costly retrofitting or complete replacement. These issues are particularly critical in multi-step processes such as fermentation, leavening, and baking, where real-time data collection from heterogeneous equipment is essential but technically demanding.

The use of blockchain and other traceability systems also raises regulatory and ethical concerns, particularly regarding GDPR compliance and food safety laws. Blockchain's immutable nature complicates the correction of erroneous or sensitive data, potentially conflicting with food recall protocols. In parallel, cybersecurity risks increase as production systems become more connected, with threats that may compromise operational continuity and customer trust (Erdogan *et al.*, 2023).

Finally, digital platforms can be difficult to scale or adapt to artisanal workflows. While large industrial bakeries may benefit from tailored ERP systems and AI-driven tools, smaller producers often face rigid or overly complex software. Moreover, artisanal production requires flexibility in recipes, fermentation times, and product formats—capabilities that many automation platforms are not yet equipped to handle.

From Industry 4.0 to 5.0 in Bakery: Emerging Needs

While the digital transformation of the bakery sector has so far been driven by the principles of Industry 4.0—automation, interconnectivity, data analytics, and system integration—an increasing number of initiatives are now shifting toward the more human-centric and sustainability-oriented framework of Industry 5.0 (Melesse *et al.*, 2025). This new paradigm does not replace digital innovation but reframes its purpose, prioritizing technologies that collaborate with human creativity, respect artisanal values, and contribute to environmental and social goals.

Unlike Industry 4.0, which emphasizes process efficiency and machine-to-machine communication, Industry 5.0 places the human operator at the heart of the production systems, equipping them with tools that augment rather than replace their expertise (Granata *et al.*, 2024). In bakery contexts, this translates into decision-support technologies for traditional processes—such as fermentation, leavening, and baking—that preserve artisanal diversity (Lodi *et al.*, 2021). For example, smart monitoring tools providing real-time data on dough behavior, temperature profiles, or optimal timing can enhance product quality while maintaining manual control (Baire *et al.*, 2019).

This approach is also closely aligned with sustainability and climate-resilience objectives. Digital solutions are increasingly applied to reduce energy and water use, minimize food waste, and optimize supply chain management (Melesse & Orrù, 2025; Singh *et al.*, 2025). At the same time, innovations such as upcycled flours and locally sourced raw materials help lower the environmental footprint baked goods production, while improving nutritional value and enabling product differentiation. These strategies support circular-economy principles and respond to growing consumer demand for clean-label, functional products (Vargas & Simsek, 2021; Guo *et al.*, 2024).

While advanced automation is still more common in large-scale production, Industry 5.0 encourages inclusive innovation through low-cost, flexible, and open-source solutions suitable for small bakeries and research environments (Melesse *et al.*, 2025). For instance, monitoring systems using ESP32 microcontroller and various sensors offer affordable real-time process monitoring (Sneiheh & Shabaneh, 2023; Akbar *et al.*, 2024; Kalamaras *et al.*, 2025; Tailor *et al.*, 2025). When combined with mobile interfaces, these systems may deliver actionable insights with minimal infrastructure—empowering small producers to innovate without compromising their identity or autonomy.

At its core, Industry 5.0 promotes co-creation between humans and machines. In the bakery sector, this means selectively integrating digital tools without eliminating the artisan's role. This dual approach not only supports operational efficiency but also aligns with consumer expectations, as customers increasingly value transparency, quality, and product origin, while continuing to associate bread with tradition, care, and craftsmanship (Melesse & Orrù, 2025).

Outlook and Research Continuity

The digital transformation of the bakery sector has evolved beyond automation and productivity gains. In the transition from Industry 4.0 to Industry 5.0, technological innovation increasingly prioritizes sustainability, human–machine collaboration, and the preservation of artisanal quality. Achieving these objectives requires scalable, inclusive solutions—particularly suited to SMEs.

One promising avenue is the adoption of low-cost, modular sensor systems for real-time monitoring and control of critical process parameters. Microcontroller-based platforms integrated with sensors offer accessible and adaptable solutions that support the human-centric and environmentally responsible vision of Industry 5.0.

The next chapters describe the design and experimental application of a smart monitoring system for dough leavening, aimed at assessing the effect of substituting gluten-free flour with varying percentages of legume-based flour. This approach supports data-driven process control and promotes the use of sustainable ingredients, thereby contributing to improved nutritional quality, reduced waste, and inclusive innovation in bakery production.

By combining digital precision with functional food innovation, this research demonstrates how smart plant management can drive technological progress while meeting the evolving expectations of modern consumers—paving the way toward a more sustainable and human-centered bakery industry.

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Advances in Gluten-Free Breadmaking

3

From Challenges to Innovation

Introduction

As discussed in the previous chapter, the baking sector is undergoing profound change, shaped by the transition from Industry 4.0 to Industry 5.0, where digitalization, sustainability, and human-centered values converge. Within this evolving framework, gluten-free breadmaking has emerged as one of the most dynamic and challenging areas of research and development.

The once small gluten-free (GF) food market has experienced rapid growth in recent years and has become a global trend. This expansion is driven not only by greater awareness of gluten-related disorders—especially celiac disease (CD)—but also by the widespread belief that GF products are a "healthier" option. As a result, demand for GF products has intensified, stimulating research to develop foods that closely resemble their gluten-containing counterparts (GCC).

Gluten is a complex protein network that plays a crucial role in determining the unique rheological properties of dough, as well as the texture and final structure of leavened baked goods (Biesiekierski, 2017; Cappelli *et al.*, 2020). Its absence makes the production of high-quality gluten-free bread (GFB) particularly demanding, especially given the growing number of individuals with celiac disease and those voluntarily adopting a gluten-free diet (Arif *et al.*, 2025).

Despite considerable research efforts and significant market growth, several challenges persist, such as enhancing the technological, sensory, and nutritional quality of GF products, extending their shelf life, reducing production costs, and ensuring wider market availability. For people with gluten-related disorders, expanding the range of healthier and more palatable GF foods is essential not only for dietary satisfaction but also for better nutrition, overall health, and quality of life.

In this context, the present chapter examines the main aspects of GFB development, addressing market trends, technological challenges, and strategies aimed at improving product quality. It reviews ingredients and processes that contribute to bread structure, texture, and nutritional profile, and discusses consumer perceptions and expectations. The chapter also considers recent scientific advances and emerging perspectives, thereby offering a comprehensive overview of the current state of gluten-free breadmaking and its future directions.

Gluten-Free Diet and Market Trends

The term gluten-related disorders (GRD) refers to a spectrum of immune-mediated diseases triggered by the ingestion of gluten proteins in genetically susceptible individuals, including CD, non-celiac gluten sensitivity (NCGS), wheat allergy (WA), gluten ataxia (GA), and dermatitis herpetiformis (DH). These disorders are characterized by both intestinal and extra-intestinal symptoms (Verdelli *et al.*, 2023), including skin manifestations (Didona *et al.*, 2025). Over the past two decades, CD has emerged as a major global public health concern, with a prevalence of 1.4% based on serologic testing and 0.7% based on biopsy confirmation (Singh *et al.*, 2018). Patients with untreated CD are at an increased risk of developing viral and bacterial infections (Asri *et al.*, 2024). For individuals suffering from CD, GA, NCGS, and DH, the only effective treatment to date is the complete and lifelong exclusion of gluten from the diet (El Khoury et al., 2018; Difonzo *et al.*, 2021).

The *Codex Alimentarius*, a collection of international food safety standards, established in 2008 a threshold of 20 ppm (mg of gluten per kg of product) for products labeled as “gluten-free” (Codex Alimentarius Commission, 2008). According to Commission Implementing Regulation (EU) 828/2014, a product can be labeled as “gluten-free” if it contains less than 20 mg/kg of gluten. In addition, there are so-called “very low gluten” foods, which are products that consist of gluten-containing cereals, but whose gluten content has been lowered to 100 mg/kg (González *et al.*, 2025). The GF food market therefore plays a crucial role in supporting individuals with GRDs, enabling adherence to a daily GF diet while also improving nutritional intake, health, and psychosocial well-being (Bascuñán *et al.*, 2017; Xhakollari *et al.*, 2019).

In recent years, the GF food industry has undergone a remarkable transformation, rising from a niche market to a mainstream phenomenon (Capriles *et al.*, 2021; El Khoury *et al.*, 2018; Xhakollari *et al.*, 2019). The global market for GF products was valued at USD 6.45 billion in 2022 and is projected to expand at a compound annual growth rate (CAGR) of 9.8% between 2023 and 2030 (Gluten-free products market size and share report, 2030). The increased demand for GF products has been attributed not only to CD patients, but also to healthy individuals who follow a GF diet, due to their belief that these products are healthier, lower in calories, and less processed, known as the “health halo” (Christoph *et al.*, 2018; Prada *et al.*, 2019). Nevertheless, to date, there is no scientific evidence supporting the health benefits of GF diets in individuals without gluten-related disorders (El Khoury *et al.*, 2018; Brouns *et al.*, 2019).

Despite the expansion of the GF market, these products remain significantly more expensive than their GCC (Hanci & Jeanes, 2018; Lee *et al.*, 2019). In the United States, which currently leads the global GF food market, large-scale industrial production has contributed to greater availability and a reduction in overall costs during the past decade (Lee *et al.*, 2019). However, both availability and affordability still represent a burden for consumers with gluten-related conditions.

The increasing popularity of GF diets has stimulated extensive research aimed at developing GF products that closely resemble their GCC equivalents. Among these products, bread has received by far the greatest research attention.

Technological and Nutritional Challenges in Gluten-Free Breadmaking

For more than 10,000 years, wheat has been a cornerstone of human nutrition and food security, and it remains one of the most important staple crops worldwide (Reynolds & Braun, 2022). Gluten, a complex mixture of hundreds of related but distinct proteins found in wheat—mainly gliadin and glutenin proteins—plays a crucial role in determining the viscoelastic properties of dough in breadmaking (Ooms & Delcour, 2019; Pourmohammadi *et al.*, 2023) and cannot be replaced by a single ingredient. In gluten-free breadmaking, however, this fundamental component of bread structure and quality is absent. The lack of gluten profoundly affects dough properties, the breadmaking process, and the final quality and shelf life of GFB (El Khoury *et al.*, 2018; Capriles *et al.*, 2021). As a result, producing high-quality GFB remains a major challenge for food scientists and producers, with increasing demand due to the growing number of individuals following a GF diet (Capriles *et al.*, 2021).

Despite advances in formulation and process optimization, GFB still tends to exhibit inferior characteristics compared to its wheat-based counterparts. Gluten-free bread is generally recognized as a product with less satisfactory appearance, texture, and flavor. It is also characterized by poor nutritional quality, short shelf life, and limited availability, while costing considerably more than GCC (do Nascimento *et al.*, 2014; Singh & Whelan, 2011; Fry *et al.*, 2018; Hanci & Jeanes, 2018; Lee *et al.*, 2019). As a result, numerous studies have focused on the development and quality improvement of GF breads (Bender & Schönlechner, 2020; Capriles *et al.*, 2021).

Gluten-Free Ingredients and Additives

White rice and maize flours are the main starchy materials employed in GFBs, often combined with maize, potato, and cassava starches (Capriles & Areâs, 2014; Masure *et al.*, 2016), and they remain the predominant ingredients in commercially available GFBs (Santos *et al.*, 2019; Roman *et al.*, 2019), because they are widely available, inexpensive, and have mild taste and flavor. However, these flours and starches have minimal structure-building potential and, thus, are frequently used along with proteins, hydrocolloid binding agents and other additives to improve GFB physical properties, acceptance and shelf-life (Capriles & Areâs, 2014).

The basic formulation of GFB typically consists of starches combined with water (generally 70-110% of flour weight), baker's yeast, sugar, salt, and vegetable oil. However, this mixture exhibits uneven gas retention, leading to irregular and unstable cell structures. These limitations often result in inconsistent processing performance and post-baking quality defects, such as a pale and cracked crust, low loaf volume with insufficient cellular structure, a dry, crumbly, and grainy crumb texture, unsatisfactory mouthfeel and flavor, and shortened shelf life (Capriles *et al.*, 2021).

To address the technological limitations of GFBs, several strategies have been investigated, including specific baking and storage technologies, alongside the incorporation of various ingredients and additives. Consequently, formulations, processing methods, and storage conditions vary considerably, strongly influencing final product quality. For example, the effect of different ingredients on loaf volume and crumb hardness has been studied (Matos & Rosell, 2015), while hydrocolloids and dietary fibers have shown quality improvements (El Khoury *et al.*, 2018).

Polymeric compounds such as hydrocolloids, proteins, and soluble fibers are widely used as structuring agents, enhancing viscosity, water-binding capacity, dough stability, and gas retention, thereby improving volume, texture, appearance, and structure, and in some cases delaying staling (Capriles & Areâs, 2014; Zhang *et al.*, 2023).

The role of hydrocolloids is well documented (Anton & Artfield, 2008; Mir *et al.*, 2016). Hydroxypropyl methylcellulose (HPMC) is the most common, often combined with xanthan or guar gum. Their effectiveness depends on factors such as hydrocolloid source, water content, raw materials, and processing conditions (Masure *et al.*, 2016; Roman *et al.*, 2019; Santos *et al.*, 2019).

Non-gluten proteins are also incorporated to increase protein content and exploit their structuring capacity. By retaining water, they improve texture and shelf life, while their involvement in Maillard reactions contributes to enhanced color and flavor (Capriles & Areâs, 2014). Sources include dairy, eggs, legumes, and non-gluten cereals, though their impact on rheology and bread quality varies considerably (Capriles & Areâs, 2014; Conte *et al.*, 2019). Allergenicity—especially from egg and dairy—has led many commercial products to exclude them (Santos *et al.*, 2019).

Sugars provide fermentable substrates for yeast and—promoting Maillard reactions—improve crust color and flavor and render GF bread more similar to wheat bread (WB). The shorter mixing and proofing times typical of GFB production make fermentable sugars particularly important from the earliest stages of the process. (Roman *et al.*, 2019).

Vegetable oils generally increase loaf volume and crumb softness compared to fats, while also improving moistness and delaying firming (Roman *et al.*, 2019).

Salt is included in GFB formulations primarily to enhance flavor. Unlike in WB, it does not play a significant technological role in dough strengthening, handling, or yeast activity regulation, and therefore can be used at lower levels (Roman *et al.*, 2019).

To improve product quality and extend shelf life, additives such as emulsifiers and enzymes have also been investigated (Ramos *et al.*, 2021; Bender *et al.*, 2020; Pashaei *et al.*, 2025). Their effectiveness varies with flour or starch types, dosage, water content, and processing conditions (Capriles & Areâs, 2014), making results difficult to predict. Emulsifiers stabilize interfaces, promoting bubble formation and stability in dough, thereby improving structure, volume, and texture, while delaying starch retrogradation and staling (Capriles & Areâs, 2014; El Khoury *et al.*, 2018; Roman *et al.*, 2019). Enzymes can further enhance technological and sensory quality, while reducing reliance on additives. Starch-modifying enzymes such as amylase limit retrogradation and staling, improving appearance, structure, texture, and shelf life. Protein-binding enzymes, including transglutaminase (TG) and proteases, have also been evaluated for their ability to modify dough functionality and improve quality (Capriles *et al.*, 2021).

Alternative Ingredients for Nutritional Enhancement

A wide range of nutrient-dense raw materials, bioactive compounds, and functional ingredients have been explored to improve both the nutritional profile and the sensory quality of GFBs, while also diversifying available formulations (Capriles *et al.*, 2016). These ingredients can be incorporated alone or blended with conventional bases such as rice, maize, cassava, or potato starches (Capriles *et al.*, 2016; Masure *et al.*, 2016). Examples include whole flours from non-gluten cereals (rice, maize, millets, sorghum), pseudocereals (amaranth, buckwheat, quinoa), legumes (beans, chickpea, pea, soya), roots and tubers (cassava, sweet potato), as well as nuts, seeds, fruit- and vegetable-derived ingredients, and even by-products from the food industry (Capriles & Areâs, 2014). Although research has consistently shown that these nutrient-dense materials can yield breads with improved nutritional value and acceptable sensory properties (Capriles *et al.*, 2016), their application in commercial GFB remains limited, often restricted to low inclusion levels (Santos *et al.*, 2019).

The diversity of potential raw materials highlights the complexity of gluten-free formulation. More than twelve different flours and starches have been identified as applicable in GFB production (Masure *et al.*, 2016). However, their technological functionality is not uniform, as performance depends on multiple factors such as botanical origin, particle size, amylose-to-amylopectin ratio, water absorption and solubility, pasting and gelling behavior, and interactions with other formulation components (Capriles *et al.*, 2021).

Process Innovations, Shelf Life, and Safety

Gluten-free breads are generally produced using a “straight dough” process, which involves mixing, proofing, and baking in pans to ensure adequate structure and shape (Capriles & Areâs, 2014). Process parameters such as hydration level and mixing conditions—including speed, duration, and type of mixing arm—have been shown to influence dough properties and, consequently, bread quality. For example, longer mixing times have been associated with improved dough aeration during proofing and higher specific volume, particularly in highly hydrated doughs. Additional mixing stages after proofing have also been suggested as a strategy to incorporate more gas and achieve a better redistribution of bubbles within the dough (Matos & Rosell, 2015; Naqash *et al.*, 2017).

In recent years, increasing attention has been given to sourdough fermentation, which involves a flour–water mixture fermented by lactic acid bacteria (LAB) and yeast (Bender *et al.*, 2020; Ramos *et al.*, 2021). This process improves texture, flavor, nutritional value, and shelf life, thus enhancing the overall quality of GFB through mechanisms such as acidification, proteolysis, production of exopolysaccharides, and the synthesis of volatile and antimicrobial compounds (Foschia *et al.*, 2016; Nionelli & Rizzello, 2016). Sourdough fermentation can also enhance the extractability of bioactive compounds and generate functional biomolecules as part of microbial metabolism (Foschia *et al.*, 2016). Its application has already reached the commercial scale, with sourdough being reported as an ingredient in 18% of GFBs on the market, where it is mainly associated with improvements in flavor and shelf life (Roman *et al.*, 2019).

Despite these advances, GFBs generally exhibit shorter shelf life than WB, mainly due to moisture loss, crumb hardening, and microbial spoilage. Technologies such as par-baking, modified atmosphere packaging, active antimicrobial packaging, and frozen storage have been investigated as strategies to extend shelf life (Capriles & Areâs, 2014). Freezing and par-baking are particularly suitable for domestic use, as breads can be thawed or baked as needed. However, further studies are still needed to improve bread quality and assess consumer acceptance. Commercial surveys have shown that in Brazil, the majority of GFBs (83%) are marketed frozen, with shelf lives ranging from 60 to 205 days, whereas breads stored in regular packaging at room temperature last only 7–15 days, and those in modified atmosphere packaging last 20–157 days (Santos *et al.*, 2019).

Beyond technological challenges, safety remains a critical issue in GF production.

Ingredients may be contaminated with mycotoxins, heavy metals, or pesticide residues, highlighting the need for strict control along the crop production chain through preventive measures during harvesting, drying, and storage (Foschia *et al.*, 2016). In addition, gluten control must be enforced at all stages of the supply chain. Effective quality management systems, good manufacturing practices, and staff training are essential to ensure that products comply with regulatory requirements and international standards. Segregation of GF raw materials, processes, and equipment from those used with gluten-containing products is also necessary to prevent cross-contamination (*Capriles et al., 2021*).

Ingredient Composition and Nutritional Characteristics of Commercial Gluten-Free Bread

Despite the rapid growth of the GF food market, information on the nutritional composition, physical properties, and consumer acceptability of commercial GFBs remains limited. Understanding ingredient lists, nutrition facts, and labeling claims is considered crucial not only for consumers but also for healthcare professionals, researchers, and regulatory authorities (Santos *et al.*, 2019).

Recent surveys have analyzed GFBs marketed in different countries, with data mainly obtained from product packaging, retail stores, and manufacturers' or traders' websites. Since nutrition labeling regulations vary by country, not all nutrients are consistently declared. Nonetheless, these studies have provided important insights into both the ingredient composition and the nutritional quality of GFBs (Roman *et al.*, 2019; Santos *et al.*, 2019).

Commercial GFBs are typically characterized by extensive ingredient lists and numerous additives. White rice flour and maize, cassava, and potato starches represent the predominant starchy bases, often blended to exploit their complementary properties. For example, maize starch yields breads with higher volume but a dry and crumbly texture, while rice flour produces lower-volume breads but improves texture and acceptability. Cassava and potato starches, although associated with lower loaf volume, enhance crumb softness and overall palatability when incorporated into starch blends (Roman *et al.*, 2019). Maize starch offers greater standardization, while the functionality of rice flour depends strongly on grain type, milling system, and particle size. Brown rice flour is reported as the main ingredient in 3–11% of GFBs and as the second ingredient in 5% of products, yet research on its application remains limited (Roman *et al.*, 2019; Santos *et al.*, 2019).

Although nutrient-dense alternative raw materials such as pseudocereals (amaranth, buckwheat, quinoa), legumes (soya, chickpea, lentil), and other gluten-free cereals (millet, sorghum) are incorporated in most formulations, they usually appear at the end of ingredient lists and therefore make only a minor contribution to nutritional quality. Their limited inclusion is likely related to concerns regarding flavor, color, cost, and consumer acceptability. Other plant-based ingredients, including fruit, vegetables, seeds, and tubers (e.g., apple, raisins, chia, flaxseed, pumpkin, sweet potato, carrot), are occasionally used to enhance flavor, aroma, and visual appeal (Roman *et al.*, 2019; Santos *et al.*, 2019).

Hydrocolloids are among the most common additives in commercial GFBs, present in 77–94% of surveyed products (Roman et al., 2019; Santos et al., 2019). Hydroxypropyl methylcellulose (HPMC) and xanthan gum are the most commonly used, followed by other gums such as guar, psyllium, and carboxymethyl cellulose used less frequently. Additional hydrocolloids, including gelatin, alginates, agar, and carrageenan, appear in a minority of formulations (Capriles *et al.*, 2021).

Proteins are commonly incorporated into GFB formulations to improve structure, with soy representing the most frequent source, followed by egg, pea, lupine, potato, and dairy proteins (Roman *et al.*, 2019).

Sugars are widespread, present in 87% of products, though about half of formulations are produced without added sugars to meet “no added sugar” claims (Roman et al., 2019; Santos et al., 2019). Nevertheless, the absence of added sugars does not necessarily improve nutritional quality, as GFBs generally remain rich in available carbohydrates and low in dietary fiber, contributing to a high glycemic index (Capriles *et al.*, 2021).

Oils and fats, mainly vegetable oils, are almost universally included as standard components of formulation (Roman *et al.*, 2019; Santos *et al.*, 2019).

The use of food additives in commercial GFB is widespread, with preservatives, emulsifiers, and acidifiers declared on labels in 54-55%, 27-50%, and 33-48% of products, respectively (Roman *et al.*, 2019; Santos *et al.*, 2019). Among preservatives, calcium propionate is most common (22-54% of samples), followed by sorbates (11-14%) usually restricted to surface application or packaging materials to avoid interference with yeast activity. Among emulsifiers, mono- and diglycerides of fatty acids and lecithin are the most commonly employed, although other compounds are occasionally incorporated at lower frequencies (Capriles *et al.*, 2021). Acids including ascorbic, citric, lactic, tartaric, and malic acid have been reported (Roman *et al.*, 2019; Santos *et al.*, 2019). These compounds may function as preservatives and/or facilitate adequate carbon dioxide release during baking when combined with sodium bicarbonate (present in 19% of products). However, their impact on flavor and texture depends on the specific type and dosage (Capriles *et al.*, 2021). Flavorings are listed in about 30% of commercial GFBs, mainly to reproduce WB sensory attributes or mask undesirable flavors from GF raw materials (Roman *et al.*, 2019). Enzymes represent another additive category, although their presence is generally not declared on product labels (Capriles *et al.*, 2021).

A share of GFBs are produced without additives, reflecting the rise of clean-label formulations. In the surveys conducted, 17% of the products analyzed contained none (Roman *et al.*, 2019), while 5% explicitly reported being free of preservatives (Santos *et al.*, 2019). Milk and dairy ingredients were reported in a small proportion of products (6%) (Roman *et al.*, 2019), whereas lactose-free or dairy-free claims were displayed on 97% of products (Santos *et al.*, 2019).

The nutritional composition of commercial GFBs shows wide variability. Reported differences in caloric and nutrient values are associated with the diversity of formulations and product moisture, which depend on the starch/flour base, the type and level of hydrocolloids, and the incorporation of fibers. Compared to WB, GFBs typically contain lower protein and higher fat levels, while sugar and dietary fiber contents vary widely. Protein, fat, and carbohydrate values differ by up to 1.7-fold between studies, with even larger variation for sugar (2.9-fold) and dietary fiber (8.6-fold) (Capriles *et al.*, 2021).

Carbohydrates are the main macronutrient in GFBs due to reliance on rice flour and starches. Consequently, GFBs are generally low in protein and higher in fat compared with white WB (8.8 g protein and 3.3 g fat per 100 g) or whole WB (12.3 g protein and 3.5 g fat per 100 g). Carbohydrate and fiber contents are broadly comparable to WB, which provide 43.1-49.2 g carbohydrate and 2.7-6 g fiber per 100 g (Capriles *et al.*, 2021).

Lower protein levels are linked to the reduced protein content of GF flours, while higher fat content derives mainly from vegetable oils added to improve mouthfeel and delay staling, though saturated fat levels remain low (Roman *et al.*, 2019). Sugar contents are similar to WB (5.7 g in white and 4.4 g in whole), partly reduced during fermentation (Capriles *et al.*, 2021).

Dietary fiber values vary widely (0-12%), depending on fiber-rich ingredients and hydrocolloids. Increased fiber inclusion has been suggested to attenuate postprandial glycemic response, especially in CD patients with type 1 diabetes (Capriles & Arêas, 2016). Sodium levels also show wide variability (5–1292 mg/100 g), though average values are similar to WB (450-490 mg/100 g) (Capriles *et al.*, 2021). Salt is expected to be lower in GFBs since it does not serve the same technological functions (i.e., strengthening the dough, improving handling, and reducing yeast fermentation rate) as in conventional breadmaking (Roman *et al.*, 2019).

GF products are usually made from refined raw materials, and micronutrient fortification is uncommon, as reflected in commercial GFB labels (Capriles *et al.*, 2021). Nevertheless, some enriched formulations include iron (7%), B vitamins (5%), calcium (5%), and folic acid (5%) (Allen & Orfila, 2018; Roman *et al.*, 2019). Data on vitamins and minerals remain limited, despite evidence of deficiencies in protein, dietary fiber, iron, calcium, folate, and vitamin D among CD patients on a GF diet (Thompson, 2000; Thompson *et al.*, 2005; Kinsey *et al.*, 2008; Yazynina *et al.*, 2008).

Labeling practices show frequent no-added-sugar (52%) and lactose-free claims (97%), but few references to fiber (4%). No functional or health claims were observed. Most GFBs (89%) are formulated with refined rice flour and starches, while only 11% use whole rice flour, highlighting limited variability and restricted nutritional profile (Santos *et al.*, 2019). Label-derived nutrient values must be interpreted cautiously, as they are often calculated from ingredients rather than measured in finished products.

Sugar values are likely overestimated, while discrepancies between labeled and analytical fiber contents have been noted—for example, higher analytical fiber values compared with labels (Larretxi *et al.*, 2020).

Overall, reformulation of commercial GFBs is needed to reduce nutritional risks for consumers who may face higher costs for products of inferior nutritional quality under the assumption that they are healthier (do Nascimento *et al.*, 2014; Christoph *et al.*, 2018; El Khoury *et al.*, 2018; Santos *et al.*, 2019).

Consumer Perceptions and Expectations of Gluten-Free Bread

The increase in research and development activities has led to a greater availability of GF products. Nevertheless, knowledge about consumer perceptions and demands for GF foods remains limited, raising questions about whether existing products adequately meet these needs. Investigations in this area may provide valuable insights for food scientists, technologists, and industry stakeholders, enabling them to better address the needs of both celiac patients and gluten-tolerant consumers who voluntarily adopt a GF diet. A deeper understanding of the motivations underlying adherence to GF diets could also help guide gluten-tolerant individuals toward healthier food choices (Xhakollari *et al.*, 2019).

Labeling has been shown to play a significant role in shaping consumer perceptions. In one study, GF labels were associated with evaluations of products as healthier, lower in calories, and less processed, even when knowledge about GF foods was limited (Prada *et al.*, 2019). These results emphasize the influence of labeling claims on food perception.

Consumer surveys among individuals with CD have consistently highlighted sensory attributes—particularly taste—as the primary determinants of purchasing GFBs, followed by nutritional information and cost (do Nascimento *et al.*, 2014; do Nascimento *et al.*, 2017; Potter *et al.*, 2014). The most frequently reported problems include crumbly texture, dryness, and short shelf life. Consumers also expressed a favorable attitude toward the fortification of gluten-free breads with vitamins and minerals, particularly calcium, vitamin D, and iron. Furthermore, consumers emphasized the need for better texture (less crumbly and moister bread), a more intense flavor reminiscent of wheat bread, longer shelf life, lower prices, and greater product diversity (Potter *et al.*, 2014).

Evidence suggests that sensory perceptions of GFBs do not differ substantially between individuals with and without CD. In both groups, preference is positively associated with sweetness, porosity, and softness, and negatively associated with saltiness, rubbery texture, and adhesive characteristics (Laureati *et al.*, 2012).

Texture, taste, and freshness are consistently ranked among the most important sensory attributes influencing purchase decisions. Ingredient lists and nutrition facts are also positively valued, whereas price is generally considered the least satisfactory attribute, followed by availability and product variety (Alencar *et al.*, 2021).

Overall, texture and taste are the sensory characteristics most frequently failing to meet consumer expectations. The need for GFBs with improved flavor and texture is consistently reported by both celiac and non-celiac consumers (do Nascimento *et al.*, 2014; do Nascimento *et al.*, 2017; Potter *et al.*, 2014; Alencar *et al.*, 2021). Despite improvements, GFBs are still perceived as inferior to their GCC, while expectations remain for equivalence to WB in terms of quality (Potter *et al.*, 2014; do Nascimento *et al.*, 2017; El Khoury *et al.*, 2018).

Strategies to Enhance the Quality and Nutritional Value of Gluten-Free Bread

Recent advances in the development of GFBs have focused on the simultaneous improvement of technological, nutritional, and sensory properties. Flours derived from alternative raw materials, including non-gluten cereals, pseudocereals, legumes, seeds, nuts, and fruit- and vegetable-based ingredients, have been incorporated to enhance the nutritional value and bioactive compound content of GFBs, while also contributing to the diversification of formulations (Capriles *et al.*, 2016). Despite these benefits, the inclusion of alternative ingredients may modify sensory attributes such as appearance, color, texture, aroma, and taste, potentially influencing consumer acceptability. For this reason, the evaluation of sensory quality and consumer perception represents a critical component of GFB research (Capriles *et al.*, 2023).

Several literature reviews have summarized studies addressing the use of alternative raw materials and ingredients to improve the nutritional profile and bioactive compound content of GFBs, while also investigating their effects on physical, sensory, and nutritional attributes, as well as potential health benefits (Capriles & Arêas, 2014; Capriles & Arêas, 2016; Capriles *et al.*, 2016). Many studies have focused on testing different ratios of alternative raw materials and assessing dough and bread quality parameters.

Recent "alternative" formulations of GFBs have demonstrated strong consumer appeal and the potential to increase the intake of whole grains, dietary fiber, and bioactive compounds. Further studies are needed to evaluate the effects of functional ingredients and processing technologies on product shelf life. It should be noted that most sensory analyses have been conducted with healthy subjects; high acceptability within this group suggests a closer similarity to regular wheat-based breads, which can be considered a favorable outcome. Nevertheless, additional sensory trials involving individuals adhering to a GF diet, particularly patients with CD, are required to confirm whether these products adequately meet their expectations.

An emerging trend, driven partly by sustainability concerns, is the enrichment of GFBs with plant-based waste and by-products rich in bioactive compounds—including dietary fiber, proteins, essential fatty acids, antioxidant compounds, vitamins, and minerals—from sources such as cereals, legumes, seeds, spices, herbs, fruits and vegetables. These materials can be exploited to reduce the nutritional deficiencies of GF products (Gomes *et al.*, 2015; Türker *et al.*, 2016; Difonzo *et al.*, 2021; Oliveira *et al.*, 2023; González *et al.*, 2025).

Given that individuals following a GF diet are at risk of nutritional deficiencies largely because the main raw materials in GFBs are low in dietary fiber, protein, B vitamins, and minerals such as magnesium, zinc, iron, and copper, research into fortification strategies is essential (Utarova *et al.*, 2024). Optimizing fortification conditions is necessary to identify compounds that deliver the greatest nutritional benefits while maintaining sensory and technological quality, bioavailability, and economic feasibility. Further investigations are needed to develop effective fortification approaches (Capriles *et al*., 2021; Utarova *et al*., 2024).

Trends and Perspective in Gluten-Free Bread Research

Gluten-free breadmaking has emerged as a growing research topic, attracting worldwide attention to the development of diverse types of GFB (Capriles & Arêas, 2014; Conte *et al*., 2019). Food scientists and technologists face the challenge of producing high-quality GFBs that more closely resemble their GCC to meet consumer demands. However, key aspects such as consumer acceptability, shelf life, and micronutrient content have not been frequent focuses of research in the past decade (Capriles *et al*., 2021).

Research on GFB remains highly heterogeneous, with considerable variability in formulation composition (types of raw materials and additives, wide ranges of water levels), processing conditions (mixing speed and time, proofing, baking), and analytical methodologies used for dough and bread evaluation (Masure *et al*., 2016). This heterogeneity complicates cross-study comparisons, but also reflects the variety of strategies adopted to improve GFBs, ranging from raw materials and ingredients to additives and technological interventions. Some studies address dough properties, shelf life, or physical, sensory, and nutritional quality, while others pursue multiple objectives simultaneously (Capriles & Arêas, 2014).

Despite significant progress in formulation strategies and insights into consumer perception, critical issues remain—including improvements in sensory and nutritional quality, extension of shelf life, cost reduction, and wider availability. Continued research and development are essential to obtain GFBs with adequate technological, sensory, and nutritional attributes, while ensuring accessibility for both individuals with gluten-related disorders and those who voluntarily follow a GF diet. Collaboration between academic institutions and the food industry is a fundamental requirement to achieve these goals.

Moreover, detailed information on formulations, nutritional composition, physical properties, and consumer acceptance of commercial GFBs is still limited. Available data reveal substantial variation in caloric and nutrient content, mainly due to differences in formulation and the extensive use of additives. Further research is required to better characterize the micronutrient profile of GFBs and to evaluate the potential role of enrichment strategies.

A notable gap persists between academic research and industrial practice. While numerous studies have demonstrated the feasibility of incorporating nutrient-dense raw materials and functional ingredients to obtain nutritionally enhanced and sensorially acceptable products, their application in commercial GFBs remains limited (Santos *et al.*, 2019). At the industrial level, discrepancies include the use of acids combined with sodium bicarbonate to improve gas retention, and the addition of flavorings to mimic the sensory profile of WB or mask undesirable flavors (Roman *et al.*, 2019).

At the same time, comprehensive sensory studies are needed to evaluate consumer perceptions and demands, both for current commercial products and for experimental formulations. These investigations should identify the key sensory attributes to be targeted for improvement, as consumers consistently report the expectation of softer, moister breads with appealing taste, appearance, and extended shelf life.

Further research is required to enhance understanding of structure formation, staling, and sensory properties in GFBs. Another important objective is the identification of reliable predictors to correlate dough parameters and physical properties of GFBs with sensory quality, both in fresh and stored breads (Capriles *et al.*, 2021).

Gluten-free breadmaking remains a complex field where the lack of gluten challenges both technology and nutrition. Considerable progress has been made in recent years through the use of alternative ingredients, functional additives, and novel processing approaches, leading to improvements in structure, texture, flavor, and shelf life. Nevertheless, key issues such as nutritional imbalance, consumer acceptance, and production costs remain open.

Looking ahead, the integration of innovative ingredients and advanced technological solutions will be crucial to further enhance the quality and sustainability of GF bread. Among these, the use of legume flours offers promising opportunities for improving both nutritional profile and dough performance (Melini *et al.*, 2017; Imam *et al.*, 2024; González *et al.*, 2025). At the same time, the application of digital tools and monitoring systems—consistent with the Industry 4.0 and 5.0 paradigms—can contribute to greater control and optimization of the breadmaking process. These aspects will be explored in the next chapter, which presents the development of an IoT-based system for real time monitoring of gluten-free dough fermentation in real time.

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IoT-Based Monitoring of Gluten-Free Dough Fermentation

4

Introduction

The basic steps identified in the breadmaking process are mixing, kneading, proofing (dough fermentation), and baking. During mixing and kneading, the ingredients are transformed into a viscoelastic matrix, while air bubbles are dispersed and act as the initial nuclei for the gas bubbles that will develop during the subsequent stages (Chevallier *et al.*, 2012; Zhang, 2023). Proofing represents the process of biochemical modification of the dough matrix by microorganisms (especially yeast and lactic bacteria) and their metabolites. During this stage, the complex microbial activity is not limited to gas production, and becomes the major driver for variations in dough rheology and, ultimately, bread quality parameters such as final loaf volume, crumb structure, texture, and flavor (Stanke *et al.*, 2014). The metabolic activity of yeast leads to the production of carbon dioxide gas, which diffuses toward the air nuclei during kneading and promotes their growth, while other metabolites contribute to flavor development in the final product. As a result, fermentation plays a decisive role in determining the overall technological and sensory properties of bread (Chevallier *et al.*, 2012; Doppler *et al.*, 2022). The viscoelastic matrix developed during mixing is able to retain the gas produced during the fermentation process, yielding an aerated crumb bread structure (Romano *et al.*, 2007). Proteins contribute to gas cells' successful expansion because they control their growth rate. Gas cells coalesce at the latest stages of fermentation, and proteins prevent an extensive creation of large cells that lead to gas losses during baking (Tsatsaragkou *et al.*, 2023).

For wheat breads, the gluten matrix is capable of maximum gas retention, while in gluten-free breads, the absence of structure-forming gluten proteins results in inherently weaker dough with poor resistance to mechanical stress and gas retention during an extended fermentation time.

Without gluten, the gases produced during fermentation are more difficult to retain, leading to reduced loaf volume and less desirable texture properties. As a result, fermentation time is reduced in gluten-free doughs, causing gluten-free bread to have generally lower palatability and a shorter shelf life compared to traditional bread (Tsatsaragkou *et al.*, 2023). Therefore, the rheological properties of gluten-free dough affect dough gas retention and tolerance to fermentation. Controlling and monitoring the dough fermentation process can boost the production of high-quality gluten-free bakery products.

Proofing time and condition—such as temperature, relative humidity, and dough expansion—also determine the quality of gluten-free bread. Low proofing temperature results in a slow fermentation, as demonstrated by low gas production and insufficient bread expansion. Higher temperatures decrease relative humidity, leading to a firmer bread crust texture (Ikarini *et al.*, 2023).

Traditional methods of monitoring dough leavening, such as manual inspection, rely on sensory cues like touch, sight, and smell to assess the dough's progress and are often inadequate, since continuous invasive measurements of dough may cause its collapse. Additionally, these methods can be subjective and imprecise, leading to inconsistencies in product quality. Decisions regarding yeast concentrations and fermentation durations often rely on the baker's experience rather than scientific research, which can lead to over- or under-fermentation, adversely affecting quality (Tebben *et al.*, 2018). These challenges highlight the need for more objective and accurate tools to ensure consistent results during dough preparation (Genzardi *et al.*, 2025). An assessment of the expansion ratio of dough during fermentation can be monitored using devices such as a rheofermentometer or by monitoring the change in dough volume over time using digital image analysis techniques (Chevallier *et al.*, 2012; Adamek *et al.*, 2023).

In recent years, the integration of digital technologies into food processing has created new opportunities for more accurate, continuous, and automated monitoring. Aligned with the principles of Industry 4.0 and the emerging paradigm of Industry 5.0, the application of IoT systems provides an effective pathway for improving process control in bakery production. IoT-based solutions enable the collection and transmission of sensor data in real time, facilitating remote monitoring and data-driven decision-making.

Against this background, this chapter introduces the development of an IoT-based system for monitoring the proofing of gluten-free dough. The proposed system employs low-cost sensors to track both environmental conditions and dough expansion, integrated with a microcontroller platform for data acquisition and wireless transmission. The ultimate aim is to design an accessible and replicable solution that not only supports experimental research but also demonstrates the potential of IoT technologies for broader application in bakery production.

System Architecture, Hardware and Software Components

The monitoring system was conceived as a low-cost, modular, and easily replicable solution to track the fermentation of gluten-free dough. The system architecture integrates environmental and distance sensors, which provide essential information for evaluating dough expansion. The collected data are transmitted wirelessly to a computer platform, offering a user-friendly interface where the progress of dough proofing can be monitored in real time through Internet of Things technology (Figure 4.1).

The main advantages of this system lie in its automation, which ensures more accurate monitoring of dough fermentation, its cost-effectiveness, as it minimizes the need for expensive laboratory equipment, and its time efficiency, achieved through continuous real-time data collection without manual intervention.

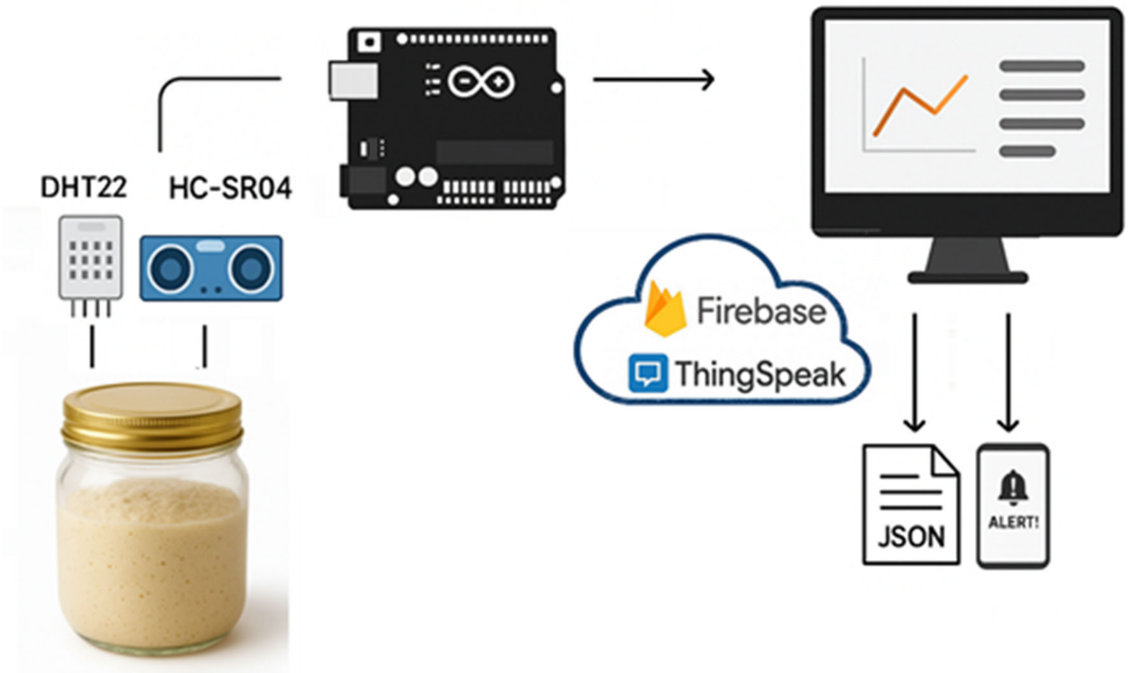

Figure 4.1. IoT Fermentation Monitoring System (AI-Generated Image).

Fermentation Unit. A glass jar from Bormioli "*Quattro Stagioni*" was selected as the fermentation chamber, with the following specifications:

- Capacity: 100 cl (33 ¾ oz)
- Dimensions: height 171 mm (6 ¾), diameter 102 mm (4)
- The jar is equipped with a screw cap with a diameter of 86 mm.

This choice provides transparency, stability, and airtight closure. The jar creates a controlled microenvironment in which dough expansion can be monitored without external interference.

Humidity-Temperature Sensor. Temperature and humidity sensors were used to measure the environmental conditions inside the fermentation chamber. These sensors are widely employed by electronics enthusiasts, as they inexpensive yet capable of delivering reliable performance. Two commonly used versions are the DHT 11 and DHT 22 (Figure 4.2).

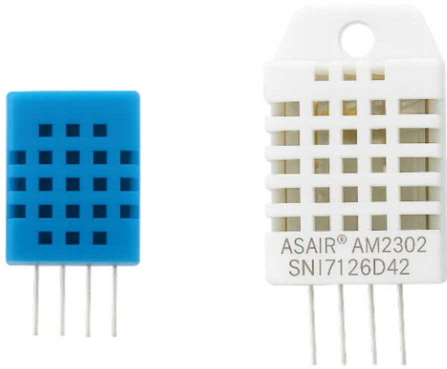

Figure 4.2. DHT11 (left) and DHT22 (right) temperature and humidity sensors, commonly used for low-cost environmental monitoring applications (AI-Generated Image).

The DHT22 is more expensive but offers superior specifications. It has a temperature measurement range of -40 to +80°C with an accuracy of ±0.5°C, compared to the DHT11's narrower range of 0 to 50°C with an accuracy of ±2°C. In terms of humidity, the DHT22 covers 0-100% RH with an accuracy of 2-5%, while the DHT11 measures 20-80% RH with an accuracy of 5% (Table 4.1).

There are two specifications in which the DHT11 outperforms the DHT22. In terms of sampling rate, the DHT11 provides one reading per second (1 Hz), whereas the DHT22 provides one reading every two seconds (0.5 Hz). In addition, the DHT11 has a more compact body size compared to the DHT22. Both sensors operate within a supply voltage range of 3-5 V, with a maximum current consumption of 2.5 mA during measurement.

Structurally, both sensors consist of a humidity sensing component, an NTC temperature sensor (thermistor), and an integrated circuit (IC) on the back side. Humidity measurement is performed by the sensing component, which includes two electrodes separated by a moisture-holding substrate. As humidity changes, the conductivity of the substrate (i.e., the resistance between the electrodes) varies. This change in resistance is processed by the IC, which converts it into a digital signal that ca be read a microcontroller.

Table 4.1 Comparison between DHT 11 and DHT 22 Sensors.

Specification	DHT 11	DHT 22 (AM2302)
Temperature range	0-50°C ±2°C accuracy	-40 to 80°C ±0.5°C accuracy
Humidity range	20-90% RH with ±5% accuracy	0-100% RH with ±2-5% accuracy
Sampling rate	1 Hz (one reading per second)	0.5 Hz (one reading every two seconds)
Body size	15.5 mm x 12 mm x 5.5 mm	25 mm x 15.1 mm x 7.7 mm
Operating voltage	3-5 V (power and I/O)	3-5 V (power and I/O)
Maximum current	2.5 mA during measurement	2.5 mA during measurement

For temperature measurement, both sensors use a NTC thermistor, a type of variable resistor whose resistance changes with temperature. Thermistors are manufactured by sintering semi-conductive materials, such as ceramics or polymers, to maximize resistance changes even with small variations in temperature. The term *NTC* stands *Negative Temperature Coefficient*, meaning that the resistance decreases as the temperature increases.

Distance Sensor. The HC-SR04 is an ultrasonic sensor used for non-contact distance measurement. It operates by emitting ultrasonic waves from a transmitter, which are reflected back after striking an object, and by calculating the distance based on the time required for the echo to return to the receiver. With a measurement range of 2-400 cm and an accuracy of ± 3 mm, the HC-SR04 is widely employed in applications such as robotics and IoT for reliable, real-time distance monitoring (Meliala *et al.*, 2024).

Figure 4.3. HC-SR04 ultrasonic distance sensor module (AI-Generated Image).

Table 4.2 reports the main specifications of the HC-SR04 sensor.

Table 4.2. HC-SR04 Ultrasonic sensor.

Feature	Specification
Voltage	DC 5V
Current	15mA
Frequency	40Hz
Maximum Range	4 m
Minimum Range	2 cm
Measurement Angle	15 degrees
Trigger Input Signal	TTL pulse 10μS
Echo Output Signal	TTL signal and proportional range
Dimensions	45 x 20 x 15 mm

Microcontroller. A controller is a hardware or software unit that manages the operation of a system by processing, storing and directing the flow of data. It is often regarded as the brain of control systems. The most commonly used types for control operations include Programmable Logic Controllers, microcontrollers and microprocessor-based controllers.

The ESP32 (Espressif Systems Company, Shanghai, China) can function both as a microcontroller and as a Wi-Fi module, offering a powerful combination of features for IoT applications. Its main characteristics include (1) a dual-core processor, (2) integrated Wi-Fi and Bluetooth connectivity, (3) a large number of general purpose input/output (GPIO) pins, and (4) low power consumption. Designed with energy efficiency in mind, the ESP32 supports multiple sleep modes and advanced power management features, making it suitable for battery-powered or energy-constrained projects. It can also be connected to displays, touchscreens, or LED indicators to provide operators with a user-friendly interface. The ESP32 can be programmed using various frameworks and languages. The most common approach is C++ programming via the Arduino IDE, while the ESP-IDF (Espressif IoT Development Framework) offers a comprehensive set of libraries and tools specifically designed for ESP32 development (Hercog *et al.*, 2023).

The ESP32-PICO-KIT V4.1 is an ESP32-based mini development board produced by Espressif. Its dimensions are 52 x 20.3 x 10 mm (2.1” x 0.8” x 0.4”). There are three mutually exclusive ways to provide power to the board. Power can be supplied through the Micro USB port, which is the default power source, via the 5V/GND header pins, or via the 3V3/GND header pins.

At the core of this board lies the ESP32-PICO-D4, a System-in-Package (SiP) module with full Wi-Fi and Bluetooth functionalities. Compared to other ESP32 modules, the ESP32-PICO-D4 integrates in a single package several peripheral components that would otherwise need to be installed separately, namely:

- 40 MHz crystal oscillator
- 4 MB flash memory
- Filter capacitors
- RF matching links

This high level of integration reduces the need for external components, lowers assembly and testing costs, and increases the overall usability of the product.

The development board also features a USB-UART bridge circuit, which enables developers to connect the board to a computer’s USB port for flashing and debugging.

All I/O signals and system power from the ESP32-PICO-D4 are routed to two rows of 20 x 0.1” header pads positioned on both sides of the development board for easy access. For compatibility with Dupont wires, 2 x 17 header pads are populated with male pin header, while the remaining 2 x 3 header pads located beside the antenna are not populated by default, but may be soldered later by the user if required.

The Figure 4.4 shows the main components of the ESP32-PICO-KIT board and their interconnections.

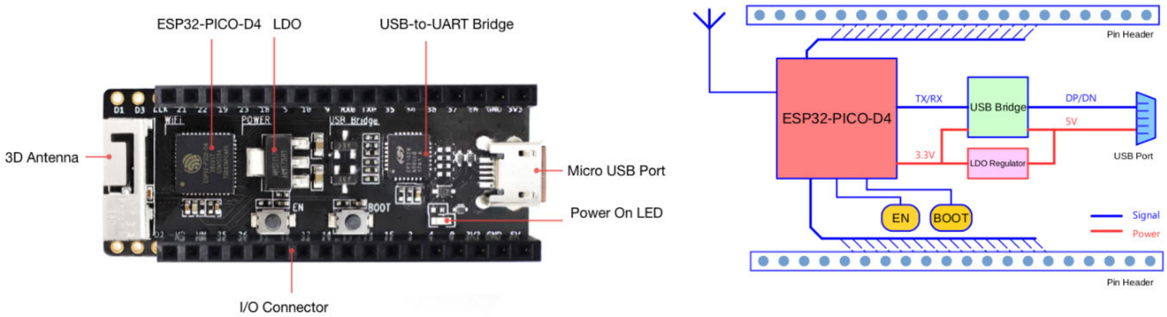

Figure 4.4. ESP32-PICO-KIT board layout (left) and block diagram (right) (https://www.espressif.com/).

Arduino IDE and the ESP32 Libraries. The firmware for this monitoring device was developed using the Arduino IDE. The Arduino IDE (Integrated Development Environment) is a software application that provides a platform for writing, compiling, and uploading code to Arduino-supported boards. It features a user-friendly interface and includes a code editor, library manager, board manager, serial monitor, and compile-and-upload tools.

The code editor is used to write Arduino sketches (programs) and offers functionalities such as syntax highlighting, auto-indentation, and code organization. The library manager enables the integration and management of additional libraries, which extend project functionality by simplifying the use of sensors, actuators, and other components. The board manager allows the installation and configuration of additional board definitions, supporting both official Arduino boards (e.g., Arduino Uno, Arduino Mega) and third-party boards such as the ESP32.

The serial monitor is a built-in tool that facilitates communication with a connected board via the serial port, allowing the transmission and reception of data between the computer and the hardware. It is primarily employed for debugging purposes. Finally, the compile-and-upload functionality translates the written code into machine language and transfers it to the board through a USB or serial connection.

Firebase Cloud System. Firebase is a cloud-hosted database provided by Google Inc. It supports various protocols, including HTTP and MQTT, making it suitable for IoT-based systems that require real-time data access. Data transmitted by IoT devices are stored in JSON format and can be accessed by users in real-time. By enabling secure access directly to the database from client-side code, Firebase allows the development of complex and collaborative applications. End users, who operate at the application layer of the IoT architecture, benefit from a responsive experience since data can be stored locally and real-time events continue to be processed even when the device is offline. Once the connection is restored, local data changes are synchronized with the remote database, with automatic merging of updates (Megantoro *et al.*, 2022; Efendi *et al.*, 2025).

ThingSpeak IoT Platform. It is a managed open-source platform used for prototyping that enables systems and devices to upload data to the Internet and perform data analysis on the uploaded data. It uses HTTPS and MQTT protocols to store and retrieve data from devices and systems. Data can be sent to ThingSpeak from a device or a system, a real-time visualization of the data created. In ThingSpeak platform, devices can be easily configured to send data to the website, the uploaded data can then be aggregated, analyzed using MATLAB and visualized in real time. Various actions can be done using apps provided by the platform.

ThingSpeak provides apps that allow us for an easier integration with the web services, social networks and other APIs. It include ThingHTTP app to interface with various web services and APIs and React app to do some actions when some conditions are met. The main component of ThingSpeak is its channel which stores data send from various devices. Each channel can save up to eight fields along with device location, url etc. The channel can be made public which can be seen by other users or private which need the API key to view the data. The private channel can be shared for some specific users.

Telegram. It is a cloud-based messaging platform focused on speed, security, and extensive features. It allows users to send messages, multimedia, and files with end-to-end encryption. Thanks to its reliable real-time communication and APIs for integration, Telegram is commonly used in IoT projects and automation, making it suitable for both personal and professional applications.

The resulting system architecture enabled simultaneous monitoring of environmental variables and dough expansion within a single controlled environment, providing a reliable basis for data collection in subsequent experimental trials. The deliberate choice of low-cost and widely available components highlights the potential of IoT technologies to be applied not only in laboratory contexts but also in artisanal and educational settings, in line with the principles of accessibility and scalability promoted by Industry 4.0 and 5.0.

System Implementation and Data Management

The microcontroller was programmed using the Arduino IDE to acquire data from the DHT11 and HC-SR04 sensors and manage wireless transmission through the ESP32's integrated Wi-Fi module. Sensor readings were collected at predefined intervals and processed into numerical values corresponding to temperature, relative humidity, and dough leavening.

To ensure real-time accessibility and secure storage, the system was connected to Firebase Realtime Database (Google). This cloud-based database employs a JSON tree structure that enables fast synchronization and cross-platform data availability. Each measurement was automatically uploaded to the database, where it could be accessed remotely from any internet-connected device. This feature allowed continuous tracking of dough behavior during fermentation and facilitated further integration with data visualization tools.

In parallel, the system was linked to ThingSpeak, an Internet of Things (IoT) analytics platform. Sensor data were transmitted to ThingSpeak channels, enabling immediate graphical representation of temporal trends. The platform also provides tools for basic data processing, MATLAB-based analysis, and export options for further statistical evaluation.

To improve usability and ensure prompt responses to critical conditions, a notification system was integrated using ThingSpeak's ThingHTTP service in combination with a Telegram bot. The ESP32 triggered a ThingHTTP request whenever a predefined condition was met (e.g., a threshold for dough expansion), and the service automatically forwarded an alert to the user via Telegram. This mechanism ensures that users receive timely notifications only when necessary, thus avoiding redundant updates and optimizing bandwidth usage.

This dual-platform approach ensures both robustness and flexibility: Firebase guarantees reliable and real-time data storage, while ThingSpeak enhances interpretability through visualization and analytical capabilities. At the same time, the Telegram notification system adds a practical alert layer, enabling proactive monitoring during experimental trials. Together, these tools provide a comprehensive environment for monitoring gluten-free dough fermentation and leavening, laying the groundwork for systematic experimental evaluation in the subsequent chapter.

The monitoring system was implemented during experimental trials of gluten-free dough fermentation. The fermentation container, equipped with the mounted sensors, was prepared by placing a fixed amount of dough at the bottom of the glass jar. Once sealed with the modified lid, the ESP32 was connected to a stable power supply via USB, and the program, compiled and uploaded via the Arduino IDE, initiated automatic data acquisition.

The DHT11 (or DHT22) recorded temperature and relative humidity inside the container at regular time intervals, while the HC-SR04 measured the distance from the sensor to the dough surface. These data were processed by the ESP32 and transmitted via Wi-Fi to Firebase Realtime Database and ThingSpeak. As a result, each measurement was securely stored in the cloud and made immediately available for remote consultation.

On the ThingSpeak platform, sensor readings were continuously updated and visualized as time-series plots, providing real-time feedback on the evolution of environmental parameters and dough leavening. This graphical interface facilitated rapid interpretation of fermentation dynamics, allowing the identification of trends such as temperature stability, humidity fluctuations, or progressive dough leavening. Meanwhile, the Telegram alert system ensured that critical changes were communicated instantly, supporting proactive decision-making.

The system proved to be straightforward to operate, requiring only basic preparation of the fermentation jar and a reliable internet connection. Once the initial preparation was complete, the setup functioned autonomously throughout the fermentation process, minimizing manual intervention and reducing the subjectivity associated with traditional monitoring methods. The data obtained were subsequently exported for statistical analysis and comparison across different experimental conditions.

Advantages and Limitations

The developed system demonstrated several advantages that make it particularly suitable for experimental research on gluten-free dough fermentation. First, it was designed as a low-cost and accessible solution, relying on widely available components such as the ESP32, DHT11 (or DHT22), and HC-SR04. This makes the system easily replicable in artisanal, educational, or small-scale research contexts, in line with the principles of accessibility and scalability. Second, the integration of real-time monitoring and cloud-based data management ensured continuous acquisition and remote accessibility of fermentation parameters, reducing the subjectivity and limitations associated with traditional manual observation. Furthermore, the modular design of the system allows straightforward adaptation and future extensions with additional sensors, such as a pH sensor, a gas sensor for CO_2 monitoring, or environmental probes.

However, several limitations must also be acknowledged. The DHT11/DHT22 sensors offer only moderate accuracy in measuring temperature and humidity, which may not capture subtle fluctuations in environmental conditions. Similarly, the HC-SR04 ultrasonic sensor, while robust and reliable for detecting dough rising, requires careful positioning to minimize errors related to irregular dough surfaces or acoustic reflections within the jar. Another limitation is its dependence on a stable Wi-Fi connection, which is essential for continuous data transmission to cloud platforms. Finally, although the system was sufficient for laboratory-scale experiments, its performance should be validated and possibly upgraded prior to implementation in artisanal baking processes.

In summary, the system offers a valuable balance of affordability, functionality, and ease of use, providing a reliable foundation for research applications while highlighting clear directions for future refinement and optimization.

Conclusion

This chapter presented the design, development, and implementation of an IoT-based system for monitoring gluten-free dough fermentation and leavening. The system combined low-cost hardware components with free cloud-based platforms to enable continuous acquisition of environmental parameters and measurement of dough expansion in real time. By integrating the ESP32 microcontroller with a DHT11 (or DHT22) temperature and humidity sensor and an HC-SR04 ultrasonic sensor, the setup demonstrated that affordable and easily accessible technologies can be effectively applied to food process monitoring.

The successful operation of the system highlights its potential as a practical tool for experimental research in gluten-free breadmaking. Beyond reducing subjectivity and manual intervention, the approach contributes to more systematic data collection and lays the groundwork for digitalization in gluten-free bakery research. While limitations related to sensor accuracy and connectivity remain, the modular nature of the system provides opportunities for further improvement, including the integration of more advanced sensors and the application of data-analytics techniques.

Overall, the developed monitoring solution represents a step toward the adoption of IoT technologies in bakery science, aligning with the broader transition toward Food Industry 5.0. In the following chapter, this system will be applied to evaluate the effect of incorporating dehulled bean flour into gluten-free bread formulations, providing new insights into the interplay between innovative ingredients, fermentation behavior, and final bread quality.

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Gluten-free Bread Improvement With Dehulled Bean Flours Using IoT Device

5

Applicative Study

Introduction

For the approximately eighty million people worldwide affected by CD (about 1% of the global population), strict abstinence from gluten-containing foods remains the only available treatment. Beyond CD, the market for GFFs is rapidly expanding, largely driven by non-celiac consumers who perceive these products as healthier alternatives. However, a recent report has highlighted that many commercially available GFFs are nutritionally unbalanced, often being high in sugars, lipids, and salt, while low in proteins and minerals, thereby increasing the risk of cardiometabolic disease. Consequently, research has shifted towards legume-based GF formulations (Imam *et al*., 2024).

The functional properties of flours play a key role in determining the quality of bakery products. In this regard, legume flours have attracted increasing attention due to their functional attributes—especially water-binding capacity and solubility index—as well as their favorable nutritional profile (Foschia *et al*., 2017). Protein deficiency has long been recognized as a bottleneck of GFFs (Belorio & Gomez, 2020). Most studies have shown that incorporating legumes into GFFs significantly enhances protein levels, more effectively than other nutrients, such as carbohydrates, lipids, and minerals. Legume crops, widely cultivated worldwide primarily for their high protein content, contain 22-40% protein on a dry weight basis, compared with 8-18% in cereals (Foschia *et al*., 2017; Carbas *et al*., 2021; Skendi *et al*., 2021; Affrifah *et al*., 2023; Messia *et al*., 2023).

Beyond proteins, legumes also are rich in minerals, vitamins, dietary fiber, and carbohydrates such as starch (Imam *et al*., 2024). Although their carbohydrate content is lower than that of cereals, they provide complex carbohydrates with prebiotic effects, including resistant and slowly digestible starches as well as dietary fiber (Maphosa & Jideani, 2017). They are an excellent source of essential minerals (iron, copper, calcium, potassium, zinc, phosphorus, magnesium, and selenium), naturally low in sodium (Höhn *et al*., 2017), and provide B-complex vitamins. Moreover, legumes are low in fat and contain no cholesterol (Maphosa & Jideani, 2017; Popoola *et al*., 2023). Their remarkable nutritional profile, combined with the presence of bioactive compounds, makes legumes a sustainable alternative to animal proteins, particularly relevant in the prevention of chronic diet-related diseases (Imam *et al*., 2024).

Nevertheless, the consumption and utilization of legumes are limited by the presence of antinutritional factors (ANFs), including lectins, tannins, raffinose, phytic acid, trypsin inhibitors, and saponins. These compounds—classified as organic acids (e.g., phytic acid), glycosides (e.g., saponins), proteins or peptides (e.g., lectins and protease inhibitors), oligosaccharides (e.g., raffinose), and polyphenols (e.g., tannins)—interfere with the absorption of minerals and amino acids, leading to reduced bioavailability and, in some cases, adverse effects (Imam *et al.*, 2024).

To improve nutritional quality and digestibility, ANFs can be reduced through processing methods such as fermentation, cooking, extrusion, microwave treatment, pressure cooking, sprouting, autoclaving, and dehulling (Popova & Mihaylova, 2019; Samtiya *et al.*, 2020; Imam *et al.*, 2024). Most ANFs are thermolabile and can be substantially reduced by heat treatment. Conversely, heat-stable compounds such as phytic acid, saponins, and tannins are more effectively mitigated by soaking, fermentation, germination, dehulling, and their combinations (Muzquiz *et al.*, 2012).

Among legumes, the common bean (*Phaseolus vulgaris L.*) stands out as one of the world's most important food legumes for direct human consumption (Asrat & Abera, 2025). It is low in fat (1-3%) and rich in proteins (15-35%), complex carbohydrates (50-60%), dietary fiber (14-19%), antioxidants, minerals (iron, zinc, potassium, magnesium, copper, calcium), and some water-soluble vitamins (Pedrosa *et al.*, 2015; Baptista *et al.*, 2017; Ganesan & Xu, 2017; Munthali *et al.*, 2022;).

However, bean seeds are also rich in non-nutrient components, such as inhibitors of proteases, lectins, anti-vitamins, saponins, tannins, and phytic acid, that hinder their utilization by minimizing the digestibility and bioavailability of essential nutrients (Romano *et al.*, 2015; Bai *et al.*, 2023). In particular, the seed coat contains higher levels of phenolic compounds compared to the cotyledon. Condensed tannins are especially abundant in the brown and black varieties, where they markedly interfere with protein digestibility by reducing hydrolysis (Romano *et al.*, 2015)

A combination of various processing techniques, including both conventional and advanced methods, is effective in reducing or inactivating ANFs. Soaking is particularly effective for the removal of water-soluble ANFs through leaching, while dehulling is an essential primary step in legume milling, yielding flours with reduced tannin content, improved digestibility, and enhanced palatability. Dehulling also markedly affects functional and pasting properties, improving technological performance (Oomah *et al.*, 2010; Moustafa *et al.*, 2013; Asrat & Abera, 2025).

Although the dehulling of beans without pre-treatments has been reported, the strong adhesion between seed coat and the cotyledons still represents a technological challenge for the food and nutraceutical industries. Compared to other legumes, dehulled beans are still poorly marketed. Dehulling efficiency is governed by seed morphology, seed size, shape, volume, uniformity, hydration capacity, and soaking ability which may be required as pre-treatment before dehulling (Anton *et al.*, 2008; Oomah *et al.*, 2010). Therefore, optimizing pre-dehulling treatments represents a promising strategy to improve the nutritional quality, functionality, and applicability of common beans in gluten-free bakery products.

Beyond the nutritional and functional properties of seeds, leguminous plants contribute to improving the biological, physical and chemical characteristics of the soil and can reduce greenhouse gas emissions. These plants have the unique ability to establish symbiotic relationships with nitrogen-fixing bacteria of the genus *Rhizobium*. Through this symbiosis, atmospheric nitrogen is converted into ammonia, a form available to plants for synthesizing organic compounds, thereby decreasing the need for mineral nitrogen fertilizers. Thus, legumes play a pivotal role in sustainable agriculture—enhancing soil fertility, reducing reliance on synthetic fertilizers, and helping to mitigate environmental challenges—while simultaneously serving as valuable sources of high-quality plant proteins (Yeremko *et al.*, 2025). Compared with cereals and animal-derived protein sources, legumes require less water, enrich soil fertility, and promote crop diversification and agroecological resilience (Yanny *et al.*, 2023).

Farmers favor common bean cultivation due to of its early maturity, nutritional value, and greater adaptability to diverse climates and soil conditions compared with other legumes. As members of leguminous crops, common beans contribute to improving soil conditions and strengthening wheat crop rotation, thereby reducing the ecological footprint of agricultural systems. Their role as a sustainable source of plant-based proteins makes them particularly valuable in the context of climate change, dietary transitions, and the growing demand for healthier and more environmentally friendly foods (Habibi *et al.*, 2025).

Thus, the inclusion of beans in GF formulations not only addresses nutritional and technological gaps but also aligns with sustainability goals, reinforcing the importance of plant-based solutions in modern food systems. Starting from the nutritional potential and technological challenges associated with the use of legumes—particularly common beans—and their antinutritional factors, the following section illustrates their practical application in GF breadmaking. Bean dehulling, previously discussed as a key strategy for improving flour functionality and digestibility, is here translated into an experimental framework, where dehulled bean flour is tested as a partial substitute for commercial GF baking mixes. In parallel, the integration of a low-cost IoT-based system for monitoring dough fermentation not only allows for enhanced process control but also demonstrates how digital tools can contribute to improving product quality and sustainability. This dual approach bridges the gap between raw material optimization and intelligent process management, laying the foundation for the experimental research presented in this chapter, which aims to improve the quality and sustainability of gluten-free bread (GFB) through the combined use of dehulled bean flour (DBF) and an IoT-based system to monitor GF dough leavening.

The specific objectives of this study were:

- optimize a pre-treatment and dehulling process for common beans in order to obtain a functional ingredient suitable for partial replacement of commercial gluten-free flour mixes;
- implement a low-cost IoT system for real-time monitoring of dough fermentation parameters (temperature, humidity, and dough rising;
- evaluate the technological and nutritional impact of dehulled bean flour addition at different substitution levels (10%, 15%, and 20%);
- assess the effects of these innovations on the quality attributes of the final bread, including physical and nutritional characteristics.

This application case therefore provides a holistic view of the entire workflow, from the raw material to the final product, highlighting how smart plant management and digital tools can be integrated into the bakery sector to support Food Industry 4.0 and Food Industry 5.0 perspectives.

Pre-treatment and Dehulling Process

Introduction

The use of legumes in bakery applications is often limited by the presence of antinutritional compounds, such as phytic acid, tannins, lectins, and raffinose family oligosaccharides, which reduce mineral bioavailability and protein digestibility. Furthermore, the intact seed coat of beans contributes to high fiber levels and influences hydration and flour functionality, thereby affecting dough development in gluten-free formulations.

To overcome these limitations, several processing methods have been proposed in the literature, including soaking, germination, fermentation, thermal processing, and dehulling. Among these, dehulling represents a particularly effective approach, as it removes the seed coat, reduces the concentration of antinutrients, and improves the technological performance of the resulting flour. In addition, pre-treatments such as soaking and drying can facilitate the dehulling process, enhancing processing yield and preserving cotyledon integrity.

In the present study, a combined approach was applied, including an optimized soaking step, controlled dehydration, and mechanical dehulling using an impact dehuller prototype. This procedure was designed to improve flour quality while maintaining the nutritional potential of beans, and to obtain a raw material suitable for incorporation into gluten-free bread formulations.

Materials and Methods

Bean samples

Fourteen genotypes of dry common beans (*Phaseolus vulgaris L.*) from different Mediterranean areas were used in the present study: IT-134, IT-206, IT-380, IT-449, IT-874, Tabacchino (IT-TAB), and Verdolino (IT-VER) (Italy); SP-171 and SP-496 (Spain); GR-430 and GR-833 (Greece); AL-924 and AL-1237 (Albania); and CR-1417 (Croatia) (Table 5.1).

Tabacchino and Verdolino are local ecotypes of Sarconi beans, protected by the

Protected Geographical Indication (PGI) denomination.

Table 5.1. Genotype code and country of origin of the fourteen bean genotypes.

No.	Genotype	Country of Origin	Image
1	00134	Italy	
2	00171	Spain	
3	00206	Italy	
4	00380	Italy	
5	00430	Greece	
6	00449	Italy	
7	00496	Spain	
8	00833	Greece	
9	00874	Italy	
10	00924	Albania	
11	01237	Albania	
12	01417	Croatia	
13	Tabacchino	Italy	
14	Verdolino	Italy	

The plant material originated from a field trial carried out in Southern Italy, at the experimental farm of Sarconi (Basilicata Region, Potenza; 40°16'20.352" N, 15°54'37.905" E). The trial was conducted in summer 2022 following local farming practices, with mechanical weed control and drip irrigation. No herbicides were applied, and the incidence of pests and diseases during the growing season was negligible.

Seeds were harvested when the pods and the seeds were fully dried, manually sorted to remove foreign matter, dust, and damaged or immature grains, and then stored in paper bags under dry conditions at room temperature (21 ± 2 °C) until further use.

Methods

Determination of physical properties of bean seeds

The tests described below were carried out on all of the bean varieties.

Characteristic dimensions of beans

Length, width and thickness of seeds

Randomly selected seeds were used to measure length (L), width (W) and thickness (T), three principal dimensions which are in the three mutually perpendicular directions (Figure 5.1) using a Vernier caliper reading to 0.01 mm. Average of ten determinations was reported.

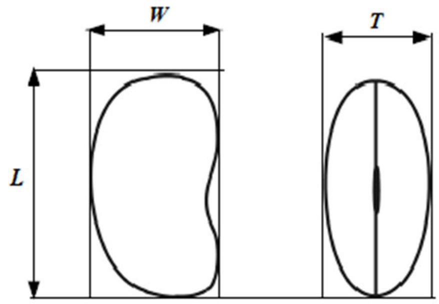

Figure 5.1. Typical dimensions of bean seeds: L–length, W–width, T–thickness (Buzera *et al.*, 2018).

Sphericity

The sphericity (U) was calculated as a function of the three principal dimensions as shown below (Mohsenin, 2020) and reported as average of ten determinations.

$$\Phi = \left[\frac{(LWT)^{1/3}}{L}\right] \times 100 \tag{1}$$

Seed volume

The volume, V (mm^3), of the seeds was calculated using the following relationship (Mohsenin, 2020) and reported as average of ten determinations.

$$V = \frac{\pi B^2 L^2}{6(2L-3)} \tag{2}$$

where $B = (WT)^{1/2}$

Surface area of seeds

The surface area, A (mm^2), of the seeds was calculated as follows (Mohsenin, 2020). Average of ten determinations was reported.

$$A = \frac{\pi B L^2}{2L-B} \tag{3}$$

Bean hull color

The surface color of seeds was measured using SA130 portable colorimeter (SAMA Italia S.r.l. ®). A glass cell containing seeds was placed against the light source, covered with a black cover and Luminance (L*), red–green component (a*) and yellow–blue component (b*) color values of the beans were recorded.

Hundred seed weight

One hundred seeds were manually counted and then weighed on a digital weighing balance with accuracy up to 0.001 mg. This analyses was performed in triplicate.

Bulk density

The AOAC method was adopted for bulk density determination. A measuring cylinder (500 mL) was filled with seeds to a height of 15 cm and then the content was weighed. This was repeated five times for each variety. Bulk density was calculated as follows (Buzera *et al.*, 2018).

$$Bulk\ density = \frac{Weight\ of\ seeds\ (g)}{volume\ of\ the\ cylinder\ (cm^3)} \tag{4}$$

Hull content and thickness

Hull content was a measure by a manual method of hull removal. A sample (10 g) of seed was soaked in 50 mL water at room temperature overnight. Water was removed and the hulls manually removed. Hulls and cotyledons were dried separately in an oven at 70°C overnight and allowed to cool at room temperature for 1 h. Dried and cooled husk was weighed and hull content was calculated.

Hull thickness was determined using a Mega-Check 10-ST thickness-meter (List-Magnetik GmbH, Germany).

Measurement of hardness

The hardness of bean half cotyledons was determined in Newtons (N) using an Instron Texture Analyzer (Instron EXTRA, Norwood, Massachusetts). The cotyledons, randomly selected, were subjected to compression at a constant speed of 10 mm/min, the compression being carried out at 70% of the initial height, using an aluminum cylinder (P25L with a 2.5 cm diameter). Ten measurements were made in each replication of the experiment, where each measurement was made on a different individual bean.

Soaking characteristics

Hydration capacity and hydration index

Hydration capacity (HC) and hydration index (HI) were determined according to Tripathi *et al.* (2012), with modifications. Fifty undamaged whole clean seeds picked randomly in triplicate from each bean variety were weighed and transferred into 1000-mL plastic measuring cylinders, and distilled deionized water at a ratio of 1 : 5 (p v^{-1}) was added to each. After keeping for 16 h, the hydrated grains were wiped using dry soft absorbent tissue to remove any extra water. The weight of beans after soaking was recorded and HC (g $seed^{-1}$) and HI calculated using the following Equations (5-6).

$$HC = \frac{W_{after} - W_{before}}{N} \quad ; \quad HI = \frac{Hydration\ Capacity}{Original\ weight\ per\ seed} \qquad (5)(6)$$

where W_{after} is the weight of 50 seeds after soaking, W_{before} is the weight of 50 seeds before soaking, and N is the number of seeds (i.e. 50).

Pre-treatment and impact dehulling

Before dehulling, dry beans were subjected to a soaking pre-treatment to facilitate hull removal and reduce the levels of water-soluble antinutritional compounds. The treatment was performed using 700 g of dried beans and the tests were carried out in triplicate. Different soaking times were tested in preliminary trials, and a soaking time of eight hours was identified as the most effective compromise between efficient hull detachment and preservation of cotyledon integrity during dehulling. Dry bean seeds were soaked in tap water at a 1 : 5 (w/v) bean-to-water ratio for 8 h at room temperature (21 ± 2 °C). After soaking, beans were drained and immediately prepared for drying. Soaked beans were dehydrated in a ventilated dryer prototype at 45 °C until they returned to their pre-soaking weight.

Mechanical dehulling was then performed using an impact dehuller prototype. Impact dehulling involves feeding bean seeds into the center of a spinning rotor that accelerates seeds and projects them against the walls of the dehuller, causing the detachment of the hull from the cotyledon. The machine is equipped with an aspiration system that removes the detached hull during/after impact, enabling collection of the hull fraction and limiting re-contamination of the dehulled cotyledons. Operating parameters, such as rotor speed (1850 rpm) and aspiration velocity (maximum setting), were set based on preliminary optimization to maximize dehulling efficiency. Before milling, the dehulled material was evaluated for dehulling yield (%), bulk density, and hardness. These parameters were used to assess the effectiveness of the pre-treatment and mechanical dehulling procedure, ensuring that the obtained raw material was suitable for subsequent use in gluten-free bread formulations. As a control, raw (untreated) beans were processed directly in the impact dehuller prototype. Under these conditions, the machine did not remove the hulls and seeds merely split into two cotyledons.

Each dehulled bean sample was ground to obtain a fine powder using a stainless-steel mill (Thermomix Vorwerk TM31, Wuppertal, Germany) at 10,000 rpm in 30 s intervals for a total milling time of 3 min. The flour samples were collected and stored in polyethylene bags at room temperature until further use.

Experimental design and statistical analysis

Results were expressed as the mean values ± standard deviation (SD). Data represent the average of three independent replicates, except for some properties, for which ten replicates were considered as specified in the Methods section. One-way ANOVA was used to test for differences among genotypes, with Tukey's post-hoc test at $\alpha = 0.05$. Pearson's correlation coefficients among seed properties were calculated to assess relationships between variables (two-tailed, $\alpha = 0.05$). Multivariate analyses included principal component analysis (PCA) and k-means clustering. Linear regression frameworks, including single- and multi-predictor specifications, and a principal component regression (PCR) approach, were applied to model the dehulling yield of common bean genotypes. Model adequacy was evaluated via R^2 and adjusted R^2, and residual diagnostics.

All analyses were performed with XLSTAT (Microsoft Excel add-in).

Results and discussion

The physical dimensions of the seeds showed a wide variability among the analyzed genotypes (Table 5.2). Seed length ranged from 10.08 mm (IT-380) to 18.54

mm (GR-430), with GR-430 and SP-496 being significantly longer than the other genotypes ($p < 0.05$). Conversely, IT-380, AL-924, and IT-449 exhibited the shortest seeds. Seed width varied between 6.58 mm (IT-380) and 10.51 mm (GR-430), while thickness ranged from 5.28 mm (CR-1417) to 7.76 mm (SP-171). Overall, genotypes such as GR-430 and SP-496 were characterized by larger seed dimensions, whereas IT-380 and CR-1417 had the smallest ones.

Colorimetric measurements (CIE Lab*) also revealed substantial differences. Lightness (L*) values varied significantly across genotypes, from 29.54 in CR-1417 to 64.43 in SP-496, indicating the presence of both very dark and very light seeds within the panel. High L* values were observed for IT-134, GR-430, and SP-496, whereas CR-1417 and IT-TAB exhibited darker seed coats. The a* parameter, associated with redness, ranged from 6.50 (GR-430) to 38.73 (IT-TAB), the latter showing a distinctly reddish pigmentation. Similarly, the b* parameter, related to yellowness, was lowest in CR-1417 (17.37) and highest in IT-TAB (34.44). Notably, IT-TAB exhibited the highest a* and b* values, indicating an intense reddish-yellow coloration of the seed coat.

Table 5.2. Dimensions and color characteristics of bean seeds.

Genotype	Lenght [mm]	Width [mm]	Thickness [mm]	L*	a*	b*
IT-134	14.77 ± 0.38^{bc}	8.64 ± 0.26^{bce}	7.52 ± 0.38^{ad}	63.73 ± 1.11^{a}	7.45 ± 0.27^{e}	21.29 ± 0.32^{ef}
SP-171	12.64 ± 0.40^{deg}	8.90 ± 0.20^{bcef}	7.76 ± 0.33^{a}	30.20 ± 2.85^{e}	16.29 ± 1.27^{cd}	19.67 ± 2.09^{ef}
IT-206	13.45 ± 0.45^{cd}	9.04 ± 0.35^{bef}	6.32 ± 0.43^{beg}	39.13 ± 1.66^{cd}	19.54 ± 1.28^{bc}	28.02 ± 1.13^{cd}
IT-380	10.08 ± 0.31^{h}	6.58 ± 0.27^{d}	5.55 ± 0.11^{bg}	62.08 ± 0.72^{a}	8.21 ± 0.40^{e}	21.97 ± 0.57^{e}
GR-430	18.54 ± 0.44^{a}	10.51 ± 0.22^{a}	5.79 ± 0.20^{bfg}	63.45 ± 2.50^{a}	6.50 ± 0.23^{e}	19.71 ± 0.63^{ef}
IT-449	11.58 ± 0.35^{efh}	8.87 ± 0.35^{bcef}	7.33 ± 0.32^{ade}	43.79 ± 1.78^{bc}	16.20 ± 0.91^{cd}	30.16 ± 0.74^{bcd}
SP-496	18.24 ± 0.50^{a}	9.64 ± 0.43^{ae}	6.52 ± 0.25^{bd}	64.43 ± 1.76^{a}	6.91 ± 0.16^{e}	20.15 ± 0.49^{ef}
GR-833	13.97 ± 0.51^{bcg}	9.97 ± 0.27^{af}	7.39 ± 0.43^{ad}	42.57 ± 1.59^{bc}	20.34 ± 1.39^{b}	33.57 ± 2.10^{ab}
IT-874	12.05 ± 0.41^{df}	7.98 ± 0.24^{bc}	5.34 ± 0.20^{g}	39.05 ± 2.00^{cd}	15.40 ± 1.23^{d}	26.57 ± 1.23^{de}
AL-924	10.47 ± 0.22^{fh}	8.51 ± 0.36^{bc}	7.10 ± 0.21^{ade}	62.07 ± 1.00^{a}	7.18 ± 0.28^{e}	20.11 ± 0.67^{ef}
AL-1237	14.58 ± 0.13^{bc}	8.76 ± 0.29^{bce}	5.64 ± 0.42^{bg}	40.97 ± 2.24^{bc}	14.99 ± 0.74^{d}	27.47 ± 1.30^{d}
CR-1417	15.27 ± 0.32^{b}	9.06 ± 0.28^{bef}	5.28 ± 0.35^{g}	29.54 ± 2.18^{e}	13.35 ± 1.66^{d}	17.37 ± 2.39^{f}
IT-TAB	12.13 ± 1.00^{d}	8.02 ± 0.57^{bc}	6.79 ± 0.36^{adef}	33.78 ± 1.81^{de}	38.73 ± 2.85^{a}	34.44 ± 1.38^{a}
IT-VER	11.40 ± 1.24^{efh}	7.78 ± 0.75^{c}	7.05 ± 0.60^{ade}	45.60 ± 1.85^{b}	13.31 ± 1.33^{d}	31.91 ± 1.61^{ac}

Values expressed are mean ± standard deviation.
Means in the same row followed by different superscript are significantly different at $p \leq 0.05$.

Collectively, morphological and colorimetric descriptors clearly discriminated the studied genotypes. GR-430 and SP-496 stood out for their larger seed size, while IT-TAB was distinguished by its strong pigmentation.

These findings highlight the role of genetic background in driving variation in seed morphology and hull color, in agreement with previous studies reporting high phenotypic diversity among common bean accessions, with seeds of different shapes, colors and sizes (Wani *et al.*, 2017; Nasar *et al.*, 2022; Kouam *et al.*, 2023; de Paula *et al.*, 2024).

Table 5.3. Technological properties of bean seeds.

Genotype	Hundred-seed weight [g]	Hull content [%]	Hull thickness [µm]	Bulk density [kg/L]	Hardness [N]
IT-134	52.80 ± 0.98^{c}	7.08 ± 0.56^{bc}	80.43 ± 8.50^{ab}	0.717 ± 0.007^{fg}	100.47 ± 13.51^{ab}
SP-171	44.33 ± 2.03^{de}	6.38 ± 0.62^{b}	57.14 ± 10.28^{bc}	0.772 ± 0.007^{d}	144.45 ± 32.48^{a}
IT-206	41.86 ± 0.61^{def}	7.96 ± 0.74^{abc}	76.21 ± 2.99^{ab}	0.741 ± 0.011^{ef}	81.57 ± 10.57^{ab}
IT-380	20.42 ± 1.03^{h}	8.28 ± 0.68^{ac}	77.65 ± 5.52^{ab}	0.842 ± 0.011^{a}	81.36 ± 20.48^{ab}
GR-430	72.17 ± 1.30^{a}	7.49 ± 0.77^{abc}	87.32 ± 7.39^{a}	0.728 ± 0.007^{fg}	92.04 ± 15.62^{ab}
IT-449	34.12 ± 1.94^{g}	8.61 ± 0.54^{ac}	82.29 ± 3.58^{ab}	0.767 ± 0.010^{d}	110.59 ± 15.14^{ab}
SP-496	60.41 ± 2.13^{b}	8.09 ± 0.57^{abc}	87.48 ± 7.63^{a}	0.711 ± 0.011^{g}	95.19 ± 54.78^{ab}
GR-833	46.99 ± 0.93^{cd}	7.64 ± 0.43^{abc}	82.20 ± 11.44^{ab}	0.718 ± 0.008^{fg}	129.74 ± 19.94^{a}
IT-874	33.94 ± 0.56^{g}	9.11 ± 0.59^{a}	77.05 ± 5.07^{ab}	0.807 ± 0.011^{b}	94.65 ± 9.81^{ab}
AL-924	41.15 ± 2.88^{def}	7.14 ± 0.73^{bc}	71.02 ± 10.42^{ab}	0.777 ± 0.008^{cd}	107.63 ± 14.23^{ab}
AL-1237	36.40 ± 2.68^{fg}	8.18 ± 0.80^{abc}	71.65 ± 5.75^{ab}	0.736 ± 0.007^{eg}	44.32 ± 4.92^{b}
CR-1417	39.91 ± 0.21^{efg}	8.99 ± 0.69^{a}	83.14 ± 9.47^{a}	0.682 ± 0.010^{h}	93.50 ± 13.41^{ab}
IT-TAB	35.76 ± 4.13^{fg}	6.81 ± 0.18^{bc}	40.32 ± 12.84^{c}	0.760 ± 0.012^{de}	90.95 ± 26.91^{ab}
IT-VER	38.45 ± 3.82^{efg}	6.42 ± 0.21^{b}	32.68 ± 11.52^{c}	0.805 ± 0.011^{bc}	95.57 ± 26.11^{ab}

Values expressed are mean ± standard deviation.
Means in the same row followed by different superscript are significantly different at $p \leq 0.05$.

Technological properties also differed markedly among genotypes (Table 5.3). Hundred-seed weight (HSW) spanned more than a 3.5-fold range, from 20.42 g in IT-380 to 72.17 g in GR-430, with GR-430 and SP-496 forming the heaviest class (p <

0.05), consistent with their larger linear dimensions reported above. Intermediate values were observed for GR-833 and SP-171, whereas IT-380 and IT-874 showed the lowest HSW.

Hull traits varied independently of seed mass. Hull content ranged from 6.38–9.11%, with IT-874 and CR-1417 at the upper end and SP-171/IT-VER at the lower end. Hull thickness was highest in GR-430 and SP-496 (≈87 µm) and clearly lower in IT-TAB and IT-VER (≈33–40 µm), indicating potentially easier dehulling for the latter group despite comparable hull percentages.

Bulk density refers to the amount of mass per unit volume of a material, including both solid material and any void spaces between particles, and depends on the solid density and on particle geometry, size and, surface properties (Wani *et al.*, 2017). Statistically significant differences were observed in bulk density, spanning a relatively narrow yet meaningful interval (0.682–0.842 kg L^{-1}). The densest seeds were IT-380 and IT-VER, whereas the lowest bulk densities were observed for CR-1417, SP-496 and IT-134. Notably, IT-380 combined low HSW with the highest bulk density, suggesting compact seed structure; conversely, SP-496 paired high HSW with low bulk density, consistent with a more voluminous morphology and lower packing efficiency.

The hardness measured on raw half-cotyledon specimens exhibited pronounced differences. SP-171 and GR-833 constituted the hardest group, significantly exceeding AL-1237, which showed the lowest mean hardness; the remaining genotypes fell in an intermediate class. The absence of a consistent association between hardness and HSW indicates that mechanical response is not mass-dependent but likely reflects hull structure and internal architecture. This observation is consistent with prior reports documenting varietal differences in bean hardness (Wani *et al.*, 2017), attributed to differences in hardness of the bean hull (Borji *et al.*, 2007). From a processing standpoint, harder seeds may require greater energy for size reduction, whereas thinner hulls (e.g., IT-TAB, IT-VER) may facilitate dehulling.

Such variability in the physical and functional properties of common beans is not only relevant for genetic characterization and breeding purposes but also plays a significant role in their processing and consumer appeal. Bulk density affects packaging and storage requirements, whereas color and hardness have been shown to influence consumer acceptance. Indeed, consumer preference has been shown to favor lighter-colored beans, as darker seeds are often perceived as older and harder, requiring longer cooking times and higher energy expenditure (Ahmed *et al.*, 2025; Deepana *et al.*, 2025).

To investigate the overall relationships among seed descriptors and to identify patterns of similarity among genotypes, a multivariate statistical approach was applied. The original dataset consisting of fourteen different common bean genotypes was evaluated through fourteen morphological, technological, and colorimetric variables. Pearson correlation coefficients were computed to quantify linear associations and diagnose collinearity among variables (Table 5.4). The correlation structure delineates a compact size construct: hundred-seed weight correlates positively with length ($r = 0.851$; $p = 0.0001$), width ($r = 0.839$; $p = 0.0002$), seed volume ($r = 0.900$; $p < 0.0001$) and surface area ($r = 0.899$; $p < 0.0001$). Seed volume and surface area showed a near-perfect correlation ($r = 0{,}998$; $p = 6{,}66 \times 10^{-16}$), indicating high collinearity. Taken together, the four size descriptors (length, width, volume, and surface area) measure the same latent dimension (seed size), so retaining them jointly would inflate multicollinearity and allow size to dominate subsequent multivariate analyses.

Table 5.4. Pearson correlation coefficients (r) among morphological, technological and colorimetric variables measured on 14 common bean genotypes (n = 14).

	Hundred-seed weight [g]	Hull content [%]	Hull thickness [μm]	Lenght [mm]	Width [mm]	Thickness [mm]	Sphericity [%]	Seed volume [mm³]	Surface Area [mm²]	Bulk density [kg/L]	Hardness [N]	L*	a*	b*
Hundred-seed weight [g]	1													
Hull content [%]	-0.2439	1												
Hull thickness [μm]	0.3343	0.6716**	1											
Lenght [mm]	0.8513**	0.1254	0.4908	1										
Width [mm]	0.8388**	0.0039	0.4693	0.7880**	1									
Thickness [mm]	0.1630	-0.6947**	-0.3106	-0.2037	0.1504	1								
Sphericity [%]	-0.5174	-0.3922	-0.4545	-0.8503**	-0.4251	0.6381*	1							
Seed volume [mm³]	0.9003**	-0.2387	0.3532	0.8043**	0.8953**	0.3888	-0.3870	1						
Surface Area [mm²]	0.8994**	-0.2410	0.3436	0.7966**	0.9078**	0.3981	-0.3693	0.9981**	1					
Bulk density [kg/L]	-0.6292	-0.1241	-0.4339	-0.7755**	-0.7827**	-0.0285	0.5651*	-0.7357**	-0.7489**	1				
Hardness [N]	0.1877	-0.3733	-0.0497	-0.1369	0.2420	0.6901**	0.4811	0.3369	0.3390	0.0000	1			
L*	0.3904	-0.0815	0.3833	0.2318	0.0433	0.0336	-0.1304	0.2270	0.2055	0.0781	-0.1299	1		
a*	-0.3271	-0.1686	-0.5319	-0.2717	-0.1220	0.1482	0.2384	-0.1666	-0.1594	0.0104	0.0400	-0.6905**	1	
b*	-0.3431	-0.1365	-0.4818	-0.3632	-0.1534	0.2442	0.3779	-0.1645	-0.1675	0.2178	-0.0607	-0.3742	0.7182**	1

** Correlation is significant at the 0.01 level (two tailed)
* Correlation is significant at the 0.05 level (two tailed)

Bulk density (kg L^{-1}) was negatively correlated with all size descriptors (length $r = -0.776$, $p = 0.001$; width $r = -0.783$, $p = 0.0009$; volume $r = -0.736$, $p = 0.0027$;

surface area $r = -0.749$, $p = 0.0021$) and positively correlated with sphericity ($r = 0.565$; $p = 0.035$), consistent with higher bulk density in seeds that are smaller and more nearly spherical. Sphericity is a dimensionless, scale-invariant shape descriptor that quantifies how closely a solid approaches a sphere of equal volume. In this dataset it was strongly negatively correlated with length ($r = -0.850$; $p < 0.001$), indicating that more elongated seeds were less spherical. Because sphericity can vary at comparable volume, it provides shape information that is not captured by size alone.

As regards the mechanical properties of the seeds, a positive correlation was found between seed thickness and hardness ($r = 0.690$; $p = 0.006$). Among hull traits, hull content and hull thickness were positively correlated ($r = 0.672$; $p = 0.0085$). Hull content was negatively associated with seed thickness ($r = -0.695$; $p = 0.0058$).

The three colorimetric coordinates showed the expected inter-relations (L^* with a^*: $r = -0.691$; $p = 0.006$; a^* with b^*: $r = 0.718$; $p = 0.0038$; L^* with b^*: $r = -0.374$; $p = 0.187$) and at most weak linear correlations with the morpho-technological variables (largest $|r| = 0.532$; $p = 0.050$ for a^* with hull thickness; all others $|r| \leq 0.482$, e.g., b^* with hull thickness $r = -0.482$; $p = 0.081$), indicating limited linear dependence across domains.

To limit collinearity among size descriptors, seed volume was used as the sole size variable, whereas hundred-seed weight, length, width, and surface area were excluded as redundant. The preference for volume over weight is justified by their strong linear correlation in these dataset ($r = 0.900$; $p = 1.14\times10^{-5}$) and because weight depends on geometric size and material properties (notably density and moisture), which complicates interpretation and increases collinearity with bulk density. Accordingly, a non-collinear subset of seven descriptors was retained for analysis: seed volume (size); seed thickness and hardness (mechanical properties); sphericity and bulk density; hull content and hull thickness.

Principal component analysis (PCA) is a technique for reducing the dimensionality of such datasets, increasing interpretability while minimizing information loss (Jolliffe & Cadima, 2016). PCA was performed with the standardized values of the seven selected variables. The correlation matrix was suitable for dimension reduction ($|R| = 0.00162$; Bartlett's test of sphericity $\chi^2(21) = 63.16$, $p = 4.2$

$\times\ 10^{-6}$). Two principal components (PCs) were retained according to the Kaiser criterion. Scree plot of eigenvalues against component number showed a clear elbow after the second component. PC1 (eigenvalue = 3.06) and PC2 (eigenvalue = 2.27) explained 43.7 % and 32.4 % of the total variance, respectively, yielding a cumulative explained variance of 76.1 %.

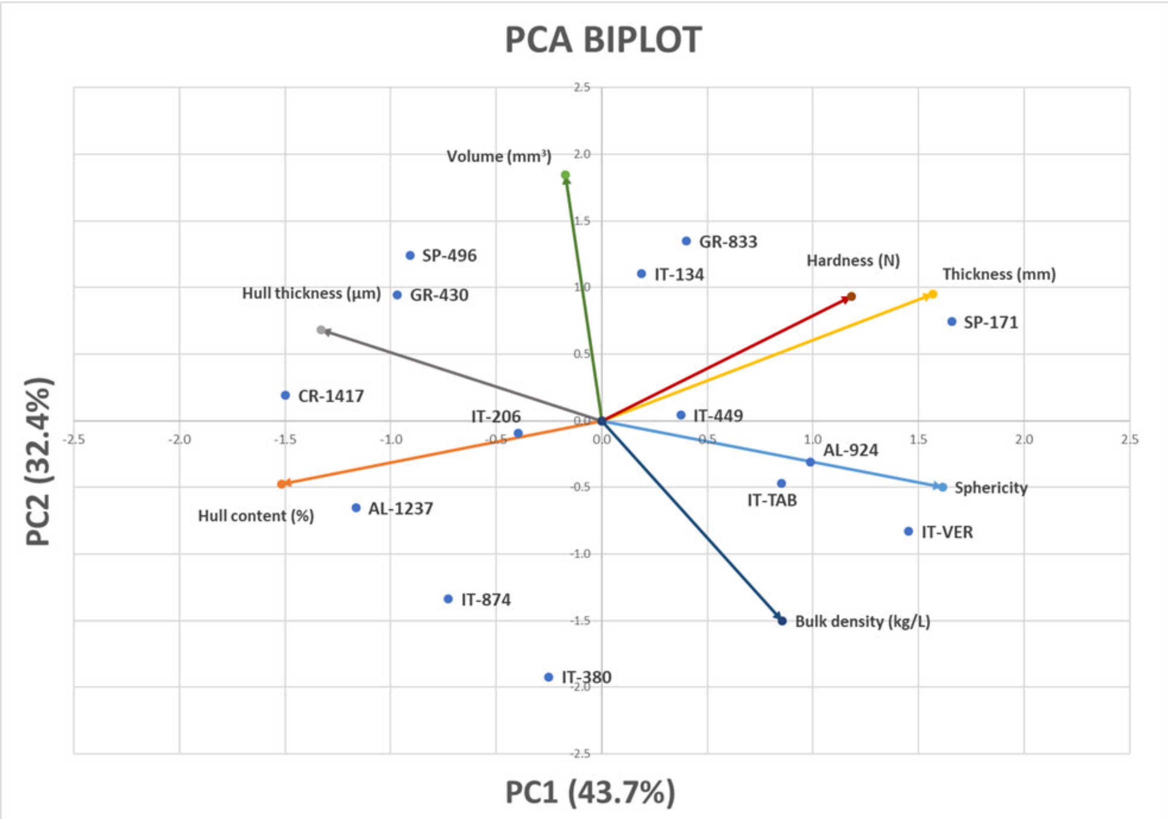

Figure 5.2. PCA biplot of the seven standardized seed descriptors across 14 common-bean genotypes. Points are genotype scores on PC1 (43.7%) and PC2 (32.4%); arrows are unrotated loading vectors. Arrow length is proportional to the loading magnitude; the angle between arrows approximates the correlation between variables. Seed thickness, hardness and sphericity load positively on PC1, whereas hull content and hull thickness load negatively. PC2 is dominated by seed volume (positive) and bulk density (negative)**.**

In the unrotated solution, PC1 captured a mechanical robustness/compactness gradient, with large positive loadings on seed thickness (0.815), sphericity (0.840) and hardness (0.616), and large negative loadings on hull content (−0.790) and hull thickness (−0.691). Accordingly, higher PC1 scores indicate thicker, more spherical, harder seeds with lower hull content and thinner hulls (i.e., reduced hull fraction and thickness), approximatively at constant size. PC2 was dominated by seed volume (0.960) and bulk density (−0.782). Hence, higher PC2 scores distinguish larger, lower-density seeds, whereas lower scores correspond to smaller, denser seeds.

The unrotated PC1–PC2 biplot (Figure 5.2) displays genotype scores together with loading vectors. Seed thickness, hardness and sphericity load positively on PC1, whereas hull content loads negatively on PC1. Seed volume loads positively on PC2, while bulk density loads negatively on PC2.

K-means clustering (k = 3) on the PC1–PC2 scores partitioned the 14 genotypes into three groups with centroids at (−0.714, −1.304), (−0.530, 0.790) and (1.065, −0.165) (PC units). In the score plot (Figure 5.3), Cluster 1 occupies the lower-left quadrant (low PC1, low PC2), Cluster 2 the upper-left (low PC1, high PC2), and Cluster 3 to the right of the origin (high PC1, PC2 near zero).

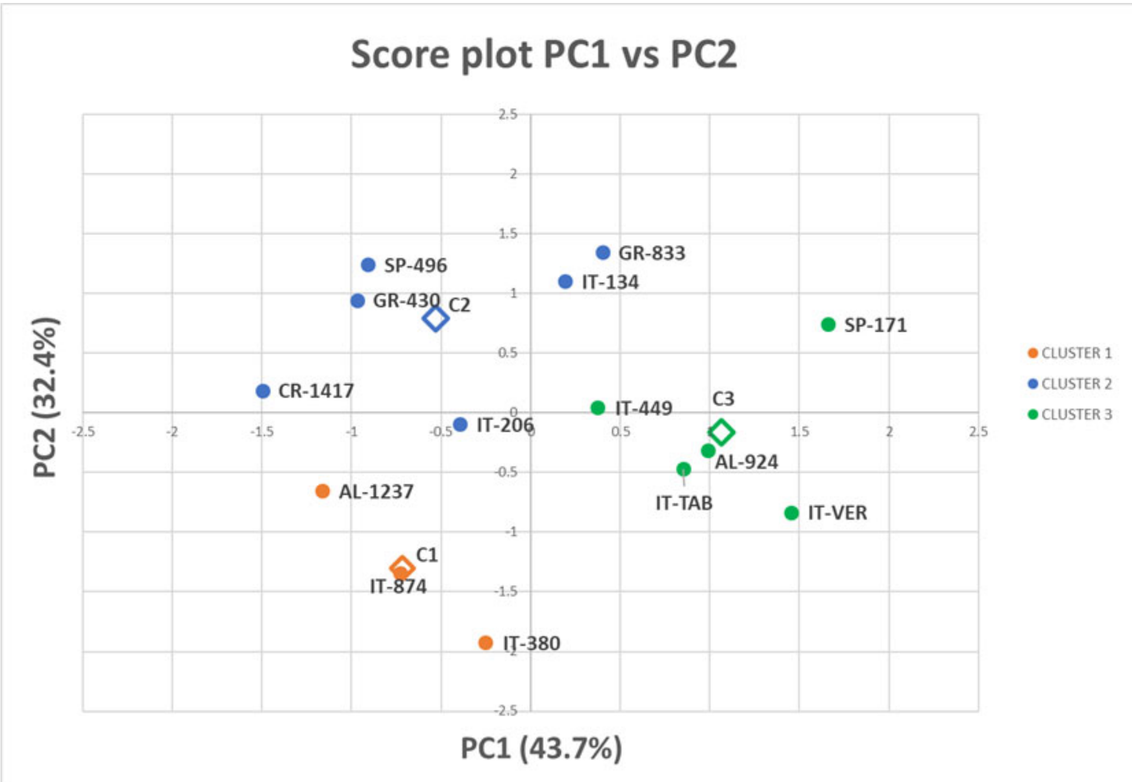

Figure 5.3. PCA score plot (PC1–PC2) with k-means centroids (diamond markers). Points (●) are genotype scores; diamonds (◇) denote cluster centroids.

Cluster 1 (IT-380, IT-874, AL-1237) occupies the negative side of both components. The mean z-score profile shows high hull content (≈ +0.90) and high bulk density (≈ +0.92) together with small size (volume ≈ −1.14), low seed thickness (≈ −1.17), and lower hardness (≈ −1.03). These are therefore small, dense seeds with higher hull content and a weak mechanical response.

Cluster 2 (IT-134, IT-206, GR-430, SP-496, GR-833, CR-1417) lies at negative PC1 and positive PC2. Its average profile indicates large size (volume ≈ +0.78) and low bulk density (≈ −0.87), thicker hulls (≈ +0.64), and lower sphericity (≈ −0.68). This group comprises larger, less-dense, more elongated seeds.

Cluster 3 (SP-171, IT-449, AL-924, IT-TAB, IT-VER) lies to the right on PC1 and slightly below the PC2 origin. Its mean z-scores show greater seed thickness (≈ +0.78), higher sphericity (≈ +0.99), lower hull content (≈ −0.74) and thinner hulls (≈ −0.90). This defines thicker, more spherical seeds with lower hull content and reduced hull thickness. Within this group, G2 sits at the upper-right edge of the PC space (high on both PC1 and PC2), G10 and G13 are closer to the PC2 origin, and G14 lies lower on PC2.

Overall, the two-component solution summarizes the multivariate structure effectively: PC1 separates seeds by mechanical robustness and compactness at a given size, and PC2 contrasts size against packing density. The three clusters in PC space align with interpretable seed profiles differing in size, density, hull content and mechanical behavior.

Variable reduction eliminated multicollinearity arising from geometric measures (e.g., volume–surface area r = 0.998), enabling PCA to summarize 76.1% of the variance with two components. With 14 genotypes, the three resulting clusters are stable and interpretable: one characterized by larger seeds with lower bulk density and thicker hulls (Cluster 2); one of smaller, denser seeds with higher hull content and lower seed thickness (Cluster 1); and a compact, mechanically more robust group with higher sphericity and lower hull content and hull thickness (Cluster 3). Given the modest sample size (n = 14), the analysis is exploratory but provides useful guidance for comparative genotype characterization.

A Principal Component Regression (PCR) approach was applied to model the dehulling yield of common bean genotypes. Four variables were selected as potential predictors based on their correlations with dehulling yield and their technological relevance: Δbulk density (Δρ), Hydration Index, sphericity, and seed length. Δbulk density is defined as the difference between post-treatment and pre-treatment bulk density (kg/L). Negative values indicate that, after soaking and re-drying, seeds became less dense (more porous) compared to their initial state. This parameter was considered alongside the Hydration Index, sphericity (a shape descriptor), and seed length (mm), as indicated by Pearson correlation coefficients, which revealed meaningful associations with dehulling yield and limited redundancy with other highly collinear traits (e.g., volume, surface area).

To reduce multicollinearity and condense the information into a smaller set of independent predictors, a PCA was performed on these four variables (n = 14 genotypes). The adequacy of the data was assessed by the Kaiser–Meyer–Olkin index (KMO ≈ 0.50, borderline but acceptable for exploratory purposes) and by the Bartlett's test of sphericity ($p < 0.05$).

PCA revealed two interpretable components (PC1 and PC2) that together explained 91.8% of the total variance. PC1 showed high and opposite loadings for sphericity (positive) and length (negative), with a secondary negative contribution from Δρ. Thus, PC1 mainly described a morphological axis, where more spherical and shorter seeds scored higher, often combined with a lower bulk density after treatment. PC2 was dominated by the Hydration Index (positive) in opposition to Δρ (negative), reflecting a hydration–structural axis contrasting seeds with higher water uptake against those showing stronger reductions in bulk density.

PC1 and PC2 were retained as predictors in a PCR model with dehulling yield (%) as the dependent variable. The regression equation obtained was:

$$\hat{Y}_{Dehulling} = 61.91 + 8.13 \cdot PC1 + 7.10 \cdot PC2$$

The PCR model achieved a good fit ($R^2 = 0.704$; $R^2adj = 0.65$; $p = 0.0012$), suggesting that about 70% of the variability in dehulling yield among the 14 bean genotypes can be explained by the combined effects of morphology, density, and hydration capacity summarized by the first two principal components (Figure 5.4).

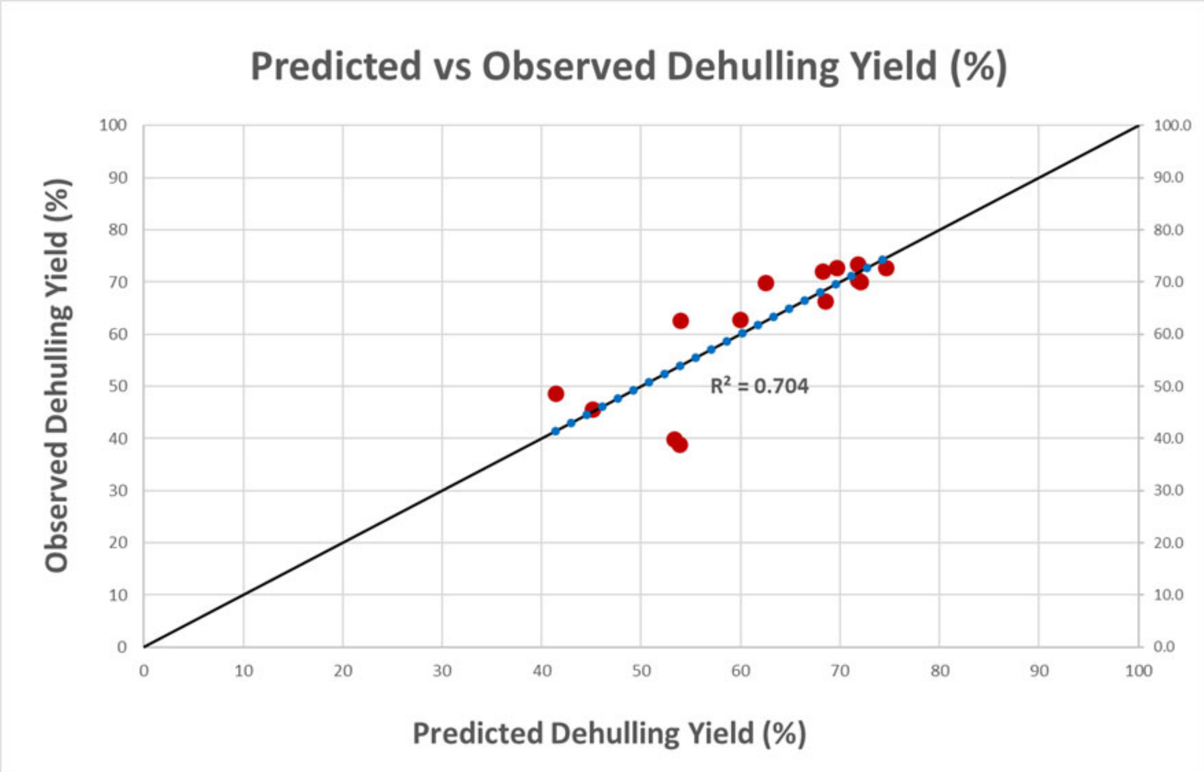

Figure 5.4. Relationship between observed and predicted dehulling yield (%) for the Principal Component Regression (PCR) model. The solid line represents the 1:1 relationship (perfect prediction), while the dashed line represents the regression fit ($R^2 = 0.704$; R^2adj = 0.65; $p = 0.0012$). The PCR model explained about 70% of the variability in dehulling yield across the 14 common bean genotypes.

Both components were statistically significant ($p < 0.01$) and residual diagnostics confirmed that standardized residuals were within ±2 and approximately distributed. This indicates that the PCR model was statistically robust despite the small sample size. Biologically, higher dehulling yield was associated with a stronger reduction in bulk density (more negative Δρ), higher hydration capacity, greater sphericity, and shorter seeds.

In addition to the PCR model, different regression models were tested to identify the best predictors of dehulling yield across bean genotypes. The univariate model based solely on Δbulk density explained 62,2% of the variability (R^2adj = 0.59) and confirmed the strong negative association between bulk density reduction during the pre-dehulling treatment and dehulling performance. This model is robust and statistically significant, highlighting Δbulk density as the most reliable single predictor of yield:

$$\hat{Y}_{Dehulling} = 14.12 - 199.26 \cdot \Delta\rho$$

The bivariate model, which included Δbulk density and seed length (mm), showed an improved fit ($R^2 = 0.686$; $R^2adj = 0.63$), with lower standard error compared to the univariate model (Figure 5.5):

$$\hat{Y}_{Dehulling} = 34.25 - 187.29 \cdot \Delta\rho - 1.28 \cdot Lenght$$

In this case, Δbulk density remained highly significant ($p < 0.01$), while seed length showed a negative but non-significant effect ($p \approx 0.16$).

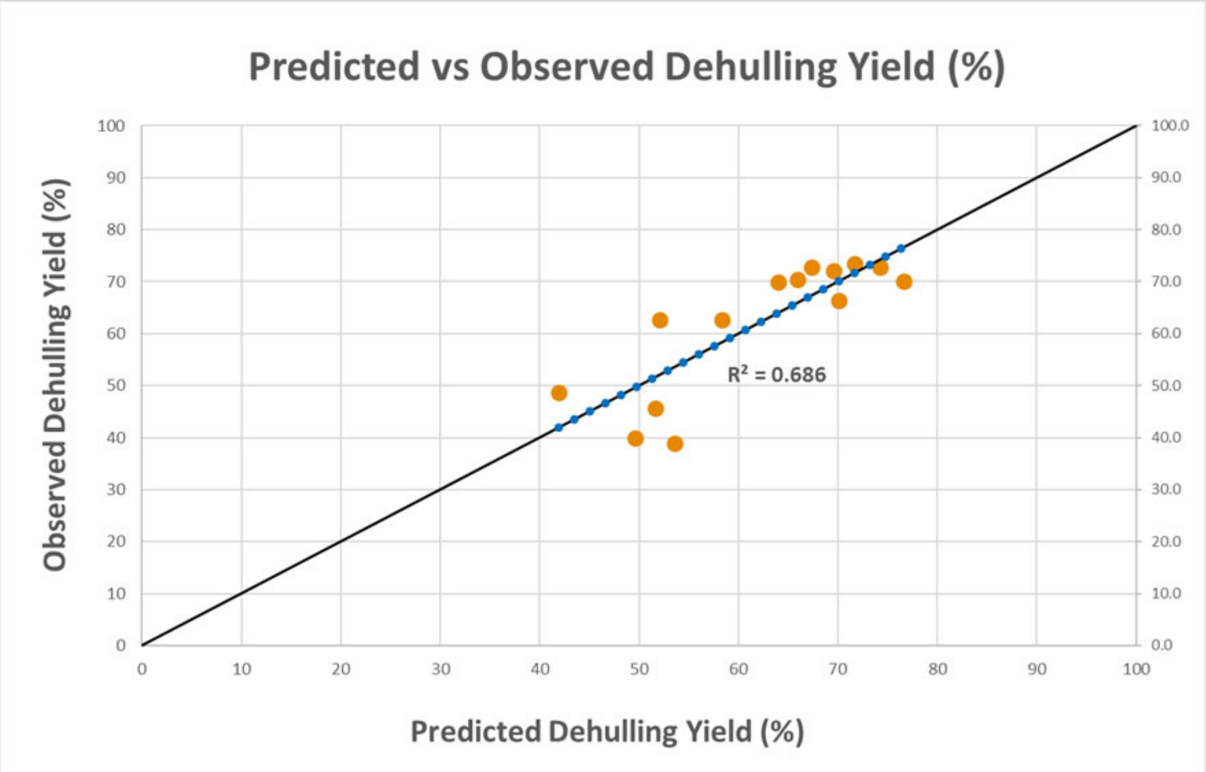

Figure 5.5. Relationship between observed and predicted dehulling yield (%) for the bivariate regression model using Δbulk density (Δρ) and seed length. The solid line represents the 1:1 relationship (perfect prediction), while the dashed line represents the regression fit ($R^2 = 0.686$; $R^2Adj = 0.629$; $p = 0.0017$). The model explained about 69% of the variability in dehulling yield across the 14 common bean genotypes.

Nevertheless, the inclusion of seed length contributed to a more accurate prediction of both medium- and high-yielding genotypes, reducing the underestimation of some observations. This model therefore represents a good compromise between predictive accuracy and parsimony.

The trivariate model, which also included Hydration Index, achieved the highest nominal R^2 (0.67) but did not substantially improve adjusted R^2 (0.57). In addition, Hydration Index and sphericity did not emerge as significant predictors ($p > 0.30$). This suggests that, although hydration dynamics and seed shape may influence husk removal, their predictive power is limited when bulk density is already accounted for.

Among all models, Δbulk density clearly emerged as the primary driver of dehulling efficiency. The bivariate model ($\Delta\rho$ + Length) provided the best balanced solution, ensuring both statistical reliability and applicability, while PCR offered the highest explanatory capacity ($R^2adj = 0.65$) at the cost of greater computational complexity. Future validation on additional bean genotypes will be essential to test the stability of these models and refine their predictive power. Expanding the dataset will also allow refinement of the model coefficients and may reveal genotype-specific responses that are not captured in the current analysis.

Real-time monitoring of gluten-free dough leavening

Dough fermentation is a crucial step in the production of gluten-free bread (GFB). In wheat bread, the gluten matrix has high gas-retention capacity, whereas in GFB the absence of structure-forming gluten proteins results in dough with poor resistance to mechanical stress and gas retention during long fermentation. As a result, fermentation times are reduced in gluten-free doughs, and monitoring and control of the fermentation process become important to ensure GFB quality (Tsatsaragkou *et al.*, 2023).

Monitoring and evaluating dough fermentation performance during breadmaking process typically involve discontinuous, destructive and costly analyses, resulting in large dataset that are costly to analyze using conventional methods. By contrast, emerging technologies offer undeniable advantages. They are fast, non-invasive, and require fewer financial resources for operation. However, the initial investment can be substantial, limiting large scale deployment (Van Kerrebroeck *et al.*, 2015; Kaffak *et al.*, 2023)). A notable advantage of a multi-sensor device is that it eliminates the need for chemical reagents during measurement, keeping the dough intact and allowing its immediate transfer to the baking stage.

This study has two distinct and interconnected purposes: (i) to validate a low-cost acquisition device, utilizing open-source IoT technology for real-time monitoring of gluten-free dough leavening; and (ii) to leverage this tool to investigate the effects of substituting commercial gluten-free flour mixes with varying percentages of dehulled bean flour (DBF) on fermentation dynamics and leavening behavior.

Materials and Methods

IoT Monitoring System

To monitor dough fermentation in real time, a low-cost IoT-based system was implemented with an ESP32 microcontroller, which provides Wi-Fi connectivity, low power consumption, and sufficient computational resources for data acquisition and transmission. The system was designed to monitor and record temperature, relative humidity, and dough rising (cm), providing continuous data throughout the fermentation process, without the need for chemical reagents and with minimal operating cost (Figure 5.6).

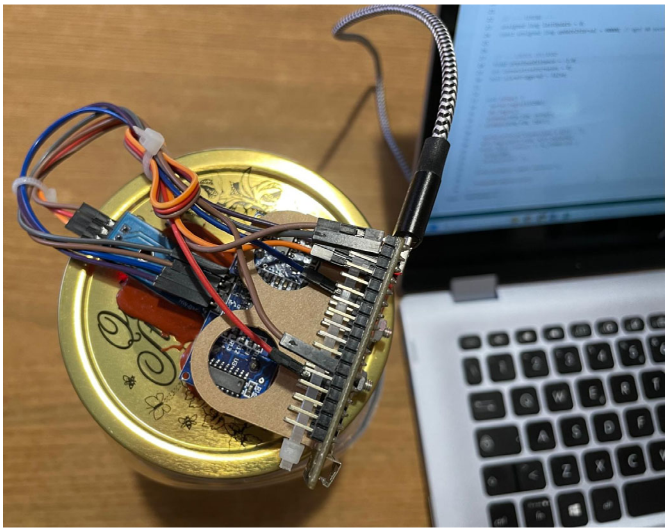

Figure 5.6. Dough fermentation monitoring device.

System components

The monitoring setup consisted of the following components:

- ESP32-PICO-KIT V4.1 development board, which serves as the central processor, controlling the sensors, acquiring and wirelessly transmitting data to the cloud database.
- DHT22 sensor module, used for measuring temperature and relative humidity inside the fermentation chamber; its compact size and digital output make it suitable for small-scale laboratory setups. Compared with the DHT11, the DHT22 provides a wider measurement range and higher accuracy, which is particularly relevant for highly hydrated gluten-free doughs.
- HC-SR04 ultrasonic distance sensor, used to measure dough height by detecting the distance from the sensor to the dough surface, allowing the calculation of dough rising in real time.
- Power Supply consisting of a 5V USB source that provides stable power to ESP32 board and sensors.

Sensor Placement and Installation

The screw cap of a Bormioli "Quattro Stagioni" glass jar was chosen to house the IoT monitoring system. A larger central opening was made in the lid for the HC-SR04 and a smaller adjacent opening for the DHT22.

To keep the two ultrasonic transducers level and perpendicular to the dough surface, the HC-SR04 was placed in the first holder and a second holder was added on top. The assembly was then secured and sealed to the lid with red silicone sealant. The DHT22 sensor module was likewise fixed to the lid with red silicone sealant, with its vents facing the interior of the jar.

The ESP32 development board was secured above the HC-SR04 holder with a cable tie. Power was supplied via a micro-USB cable.

Baseline measurements (distance with the empty jar and ambient temperature/relative humidity) must be taken before each run, and the system must be kept away from heat sources.

Data Acquisition and storage

Real-time data acquisition with an ESP32 programmed via the Arduino IDE is central to this study. Leveraging its GPIO pins and integrated Wi-Fi, the ESP32 interfaces with a DHT22 (temperature, relative humidity) and an HC-SR04 (distance) to capture continuous, non-invasive measurements of gluten-free dough fermentation and leavening.

Time-stamped records are pushed to Firebase Realtime Database (JSON-structured) for reliable, secure cloud storage and remote accessibility, and in parallel to ThingSpeak channels for immediate time-series visualization.

A ThingSpeak React rule monitors the proofing-completion flag and, when the condition is met, triggers a ThingHTTP request to the Telegram Bot API to send an immediate notification that proofing is complete.

This low-cost, scalable pipeline supports systematic, data-driven evaluation across experimental conditions, with datasets readily exportable (e.g., CSV) for downstream statistical analysis.

Table 5.5 outlines the step-by-step procedure used to configure the ESP32-based real-time monitoring system—from wiring and library initialization to cloud connectivity, real-time plotting, and alerting.

Table 5.5. Algorithm and steps for device setup and development.

Steps	Description
1. Setup and wiring	Connect DHT22 and HC-SR04 to the ESP32 (assign GPIOs for DHT data, TRIG, and ECHO), and power the board via 5 V USB. Verify stable connections after mounting.
2. Variables and configuration	Declare variables for sensor readings, timestamps, sampling interval, and alert state. Specify Wi-Fi credentials and cloud parameters (Firebase API key and database URL; ThingSpeak channel ID and write key).
3. Libraries and initialization	Include and initialize the required libraries. Start serial diagnostics, join Wi-Fi, initialize the ThingSpeak client, and open the Firebase Realtime Database session using the provided parameters.
4. Time synchronization	Enable NTP so each measurement carries a reliable, ISO-like timestamp; use a fallback string if time isn't ready.
5. Sensor readings	Read DHT22 for temperature and relative humidity. Measure distance with HC-SR04 (trigger pulse, read echo) and compute the distance in cm.
6. Data processing	Convert distance to dough rise using the baseline. Apply smoothing/outlier rejection as needed.
7. Data transmission and alerts	Push each time-stamped record to Firebase Realtime Database (JSON) and update ThingSpeak fields for real-time plots. When the alert flag is true, send the Telegram notification (via ThingHTTP).
8. Real-time monitoring and User Interface	Monitor live charts on ThingSpeak and verify incoming records on Firebase. Use Serial logs for troubleshooting and export data for downstream analysis.

System testing and validation

Prior to the fermentation trials, testing and validation procedures were performed to ensure accurate, reliable operation under realistic conditions. This included verifying correct data acquisition and processing and confirming that the system responded effectively to user inputs.

Temperature and humidity readings were cross-checked against a calibrated thermo-hygrometer placed near the headspace, while dough height was measured manually with a ruler and compared with ultrasonic readings to verify agreement.

Raw materials

The choice of raw materials plays a crucial role in the development of gluten-free bread, as the absence of gluten requires the use of alternative ingredients able to provide both functional and nutritional quality.

In this study, two main categories of raw materials were considered: (i) dehulled bean flour and (ii) two commercial gluten-free baking mixes, employed as the bases for dough preparation and breadmaking trials. These mixes consist of different gluten-free flours and starches, enriched with hydrocolloids and other technological ingredients, designed to improve dough workability and the quality of the final bread, while mimicking the texture and consistency of wheat-bread.

The legume flour used in the leavening trials was produced from the Tabacchino ecotype of Fagioli di Sarconi PGI (Protected Geographical Indication) beans grown in Basilicata, southern Italy. Aesthetic grading can cause significant food losses during marketing, as beans that are perfectly nutritious and safe for human consumption but do not meet specific standards of color, shape, or size are discarded or underutilized. Dehulling followed by milling into flour offers a practical route to valorize these non-commercial fractions, converting them into a functional food ingredient. This strategy aligns with circular-economy principles in the agri-food sector, promotes the use of local biodiversity, and contributes to a more sustainable food system.

The fermentation trials were designed to evaluate the performance of gluten-free doughs containing bean flour at different substitution levels, with real-time monitoring provided by the IoT system described above.

Commercial Gluten-Free Mixes

Two commercial gluten-free baking mixes were used in the gluten-free bread formulations (Figure 5.7):

- Mulino Caputo Fioreglut Gluten Free - 1 Kg (Antimo Caputo, Naples, Italy);

- Schär Mix B - 500 g (Dr. Schär, Burgstall/Postal - BZ, Italy).

Both products were purchased from retail supermarkets in Potenza (Italy) and used as received.

Figure 5.7. Commercial gluten-free flour mixes: Caputo Fioreglut (Caputo, Naples, Italy; left) and Schär Mix B Pane (Dr. Schär, Burgstall, Italy; right).

Both mixes consist of gluten-free cereal flours and starches, hydrocolloids (psyllium seed fiber, hydroxypropyl methylcellulose, and technological aids (dextrose, flavoring, salt) to improve dough handling and final bread quality (Table 5.6). They were used as benchmark matrices to evaluate the effects of partial substitution with bean flour in subsequent experiments.

Table 5.6. Ingredients of the commercial gluten-free baking mixes used in this study.

Product	Ingredients (as declared on the label)
Caputo Fioreglut	Gluten-free wheat starch; dextrose; maize starch; buckwheat flour; rice starch; psyllium seed fiber; thickener: guar; flavoring.
Schär Mix B Pane	Maize starch; rice flour; vegetable fibers (psyllium, bamboo); whole rice flour (3.8%); lentil flour (3.6%); dextrose; thickener: hydroxypropyl methylcellulose; salt.

Composition of gluten-free doughs

Gluten-free doughs were prepared using a commercial gluten-free baking mix as the base, with partial substitution by dehulled bean flour (DBF). Three substitution levels were tested: 10%, 15%, and 20% (w/w), replacing an equivalent proportion of the commercial mix. A control dough containing only the commercial mix, without bean flour, was also prepared.

The control formulation had been optimized in preliminary trials and served as the reference recipe for all experiments. The base formulation consisted of a gluten-free flour mix (Caputo Fioreglut or Schär Mix B, depending on the trial), Nutrifree wholemeal bread mix (NT Food S.p.A., Italy), fresh yeast (Lievital, Italy), salt (Italkali, Italy), extra virgin olive oil (De Cecco, Italy), and tap water. DBF was incorporated into the experimental formulation as a substitute for the flour mix (Table 5.7). Ingredients proportions were standardized across all trials to ensure comparability of results.

Table 5.7. Composition of experimental gluten-free doughs.

Ingredient (%)	Control	DBF10%	DBF15%	DBF20%
Gluten-free flour mix	34.0	30.6	28,9	27.2
Whole meal bread flour mix	17.0	15.3	14,5	13.6
Fresh yeast	1.0	1.0	1.0	1.0
Salt	0.5	0.5	0.5	0.5
Extra virgin olive oil	1.7	1.7	1.7	1.7
DBF	-	5.1	7.6	10.2
Water	45.8	45.8	45.8	45.8

Preparation of experimental gluten-free doughs

A straight-dough method was used to prepare the experimental gluten-free doughs (GFDs). Given the small batch size, mixing was performed in a stainless-steel bowl using a Danish whisk at room temperature (24 ± 1 °C).

The flours were first homogenized (dry blending). Yeast, previously dissolved in water tempered to 30 ± 2 °C to ensure even distribution, was then added, followed by oil and salt. Mixing continued until a smooth, uniform batter was obtained, with no visible lumps or unincorporated particles. The dough was transferred into fermentation containers (~295 g each) for subsequent monitoring. The same handling protocol was applied across all formulations to minimize variability.

Experimental Protocol

The experimental framework enabled a comprehensive evaluation of both the technological performance of DBF-substituted doughs and the suitability of the IoT monitoring system for capturing fermentation dynamics.

Each formulation (control, DBF10%, DBF15%, and DBF20%) was prepared in triplicate—yielding 12 fermentation units per commercial mix—and fermented at 25 ± 1 °C for 130 minutes, based on preliminary tests showing that maximum expansion was reached within this timeframe. No external proofing chamber was used to reproduce standard artisanal gluten-free bakery conditions. For each dough type, three 100 cL Bormioli "Quattro Stagioni" glass jars were used:

- jar 1 equipped with the IoT system;
- jar 2 fitted with a pH probe and two K-type thermocouples inserted into the dough to monitor pH evolution and internal temperature;
- jar 3 fitted with two additional K-type thermocouples (for internal-temperature reference) and two sampling needles connected to a Dansensor CheckMate 3 (Mocon Europe A/S., Ringsted, Denmark) to measure headspace O_2 and CO_2.

All thermocouples were connected to a Pico Technology TC-08 8-channel temperature data logger (Pico Technology, Cambridge, UK).

All lids were modified to accommodate the instrumentation and sealed with red silicone sealant to maintain a closed, stable fermentation environment.

Monitoring protocol and Data Collection

During fermentation, headspace temperature and relative humidity, together with dough height, were recorded at 1-minute intervals by the IoT system, enabling real-time fermentation curves from which maximum dough expansion (cm) and time to peak height (min) were derived. In parallel, pH, dough core temperature, and headspace O_2/CO_2 were measured every 10 minutes.

Statistical analysis

Objective 1

Endpoints were computed per replicate for each Mix × substitution level (0, 10, 15, 20%; three replicates per combination). Precision within each Mix × substitution level (%) was summarized by mean, standard deviation (SD), and coefficient of variation (CV). Between-mix discrimination at fixed substitution levels (Caputo vs B-mix) was evaluated using Welch's two-sample t-tests (two-sided); alongside p-values, effect sizes were reported as Cohen's d, and 95% confidence intervals where informative. In addition, within-mix extreme contrasts (0% vs 20%) were assessed using Welch's two-sample t-tests (two-sided), reporting Cohen's d and, where informative, 95% confidence intervals for the mean difference. Given the triplicate design ($n = 3+3$), interpretation emphasized effect sizes and consistency across endpoints rather than *p*-values alone. Trends across substitution levels were assessed within each mix using simple linear regressions of each endpoint on percentage (slopes, Pearson's r, two-sided *p*-values). Endpoint roles were pre-specified: H_{max} as the primary endpoint; μ_{max} and t_{50} as secondary kinetic endpoints; Rise% included descriptively given its greater relative variability when H_0 is small. Analyses were exploratory/comparative; no multiplicity adjustments were applied. Welch's tests mitigate potential variance heterogeneity.

Computations were performed in Excel using built-in functions.

Objective 2

Endpoints were computed per replicate for each Mix × substitution level (0, 10, 15, 20%; three replicates per condition). Ambient signals from the onboard DHT22 (temperature, relative humidity) were summarized per run as mean and SD. Height-based endpoints were computed as in Objective 1. To quantify potential environmental bias, simple linear regressions were fitted across all 24 runs with H_{max} as the response and, separately, temperature and relative humidity as predictors. For each regression, the slope (reported as cm/°C or cm/%RH), Pearson's r, and two-sided *p*-value were recorded. An adjusted maximum height (H_{max_adj}) was then obtained by recalculating each run's H_{max} as if it had occurred at the overall mean temperature and overall mean RH (grand mean across the 24 runs), using the fitted temperature and humidity slopes. This adjustment removes first-order T/RH effects while preserving the formulation signal. For H_{max_adj}, summary statistics (mean, SD, CV) were produced for each Mix × substitution level. Within each mix, trends with substitution were assessed by regressing mean H_{max_adj} on percentage and reporting the slope, correlation, and two-sided *p*-value.

Within-mix extreme contrasts (0% vs 20%) on H_{max_adj} were evaluated with Welch's two-sample t-tests (two-sided); alongside *p*-values, 95% confidence intervals for mean differences and Cohen's d (pooled SD) were reported. Given n = 3 + 3, interpretation emphasized effect sizes and pattern consistency over p-values alone.

To integrate final height and kinetics, a composite score was constructed by standardizing across all replicates (z-scores) H_{max_adj}, μ_{max}, and the inverse of t_{50} (higher is better), and combining them with fixed weights of 50%, 30%, and 20%, respectively. For each mix, the composite score was regressed on substitution (%) and 0% vs 20% Welch contrasts were reported. Given n = 3 per condition, interpretation emphasized effect sizes and pattern consistency rather than *p*-values alone.

All computations were performed in Excel using built-in functions.

Methods

Objective 1

Proofing tests were performed on two commercial mixes (Caputo, B-mix) with bean flour replacement at 0, 10, 15, and 20% to verify whether the IoT proofing system alone can (i) describe dough leavening kinetics, (ii) discriminate mixes and bean-flour substitution levels, and (iii) do so with acceptable repeatability across replicates.

For each Mix × substitution level, three independent replicates were acquired (n

= 3). The IoT device recorded distance over time at 10-min intervals, with each time point computed as the mean of 10 readings, and distances were converted to dough height (cm) using the empty-jar reference.

From each height–time curve, the following endpoints were derived: initial height (H_0), maximum height (H_{max}), relative expansion (Rise% = (H_{max} − H_0)/H_0 × 100), maximum growth rate (μ_{max}, cm·min^{-1}), and the time to 50% of total rise (t_{50}). The growth rate was computed as the maximum finite difference $\Delta H/\Delta t$ over the sampling interval; t_{50} was obtained by linear interpolation between the two time points bracketing the 50% level.

Objective 2

Environmental data from the DHT22 (temperature and relative humidity) were summarized per replicate as mean and SD over the proofing duration to (i) assess the stability and impact of ambient conditions on IoT height endpoints, (ii) compute an adjusted maximum height (H_{max_adj}) that neutralizes first-order temperature and RH effects so that remaining differences reflect the dough formulation (mix and % bean-flour replacement) rather than the environment; and (iii) evaluate a simple multi-criteria composite that combines H_{max_adj}, μ_{max}, and t_{50} to determine whether the combined metric improves separation between conditions.

The sensitivity of H_{max} to temperature and to RH was assessed by simple linear regressions. An adjusted endpoint was then defined as $H_{max\_adj} = H_{max} - b_T (T - T_{ref}) - b_{RH} (RH - RH_{ref})$, using the grand means as references (T_{ref} and RH_{ref}) and the fitted slopes b_T and b_{RH}. The same analyses as in Objective 1 were repeated on H_{max_adj} (group summaries, trends vs substitution within mix, and Welch comparisons Caputo vs B-mix at fixed substitution level %).

Finally, a composite score was built by z-scoring H_{max_adj}, μ_{max}, and the inverse of t_{50} (higher is better) over all replicates, and combining them with fixed weights 0.5, 0.3, 0.2 respectively; slopes vs substitution and Welch tests (0% vs 20%) were used to check whether the composite enhances discrimination.

Results and Discussion

Objective 1

Kinetic descriptors and KPIs. From each height–time profile a compact set of Key Performance Indicators (KPIs) were extracted: initial height (H_0), maximum height (H_{max}), relative expansion (Rise% = (H_{max} - H_0)/H_0 × 100), maximum growth rate (μ_{max}, cm·min^{-1}), time to half-rise (t_{50}), and time at maximum height (t_{Hmax}).

Table 5.8. Per-replicate KPIs from the IoT height–time signal. For each Mix × substitution level (%): H_0, H_{max}, Rise%, μ_{max}, t_{50}, t_{Hmax} (n = 3).

Mix	Substitution level (%)	H_0 (cm)	H_{max} (cm)	Rise%	μ_{max} (cm/min)	t_{50} (min)	t_{Hmax} (min)
Caputo	0	3.55 ± 0.88	11.59 ± 1.02	240.7 ± 92.2	0.181 ± 0.026	70 ± 0	130 ± 0
Caputo	10	3.68 ± 0.52	9.38 ± 0.64	156.5 ± 24.4	0.186 ± 0.07	63.3 ± 20.8	116.6 ± 11.5
Caputo	15	3.34 ± 0.19	9.02 ± 0.06	170.6 ± 16.9	0.184 ± 0.033	60 ± 10	96.6 ± 28.8
Caputo	20	3.32 ± 0.2	8.18 ± 0.26	146.3 ± 9.8	0.177 ± 0.063	76.6 ± 5.7	130 ± 0
B-mix	0	2.99 ± 0.52	7.92 ± 0.62	171.5 ± 58.1	0.174 ± 0.062	53.3 ± 15.2	90 ± 20
B-mix	10	3.46 ± 0.18	6.96 ± 0.36	101.7 ± 15.7	0.112 ± 0.041	50 ± 0	100 ± 10
B-mix	15	3.1 ± 0.52	7.16 ± 0.17	135.9 ± 48.6	0.101 ± 0.013	56.6 ± 15.2	103.3 ± 15.2
B-mix	20	2.98 ± 0.39	6.62 ± 0.49	125.9 ± 44.4	0.105 ± 0.019	53.3 ± 5.7	103.3 ± 11.5

KPIs were computed for both mixes (Caputo, B-mix) at four substitution levels (0, 10, 15, 20%), with three independent replicates per condition (n = 3) (Table 5.8). Across all replacement levels, Caputo achieved greater final expansion (Rise% and H_{max}) than B-mix, while B-mix reached 50% rise earlier (lower t_{50}), indicating a faster early expansion but lower gas retention at the end of proofing.

Caputo vs B-mix at the same replacement level. At 0% (control), Caputo showed markedly higher maximum height (H_{max} = 11.59 ± 1.03 cm vs 7.92 ± 0.62 cm;

p = 0.010; d = 4.31) and higher relative expansion (Rise% = 240.7 ± 92.2% vs 171.5 ± 58.1%; p = 0.344; d = 0.90), whereas B-mix reached t_{50} sooner (53.3 min vs 70 min).

At 10%, Caputo again exceeded B-mix in H_{max} (9.38 ± 0.64 cm vs 6.96 ± 0.36 cm; p = 0.010; d = 4.61) and Rise% (156.5 ± 24.4% vs 101.7 ± 15.7%; p = 0.039; d = 2.67), with a higher peak growth rate (μ_{max} = 0.186 vs 0.112 cm·min^{-1}) despite B-mix retaining a shorter t50 (50 min vs 63.3 min).

At 15%, H_{max} strongly favored Caputo (9.02 ± 0.06 cm vs 7.16 ± 0.17 cm; p = 0.001; d = 14.30), Rise% remained higher for Caputo (170.6 ± 16.9% vs 135.9 ± 48.6%; p = 0.344; d = 0.95), and μ_{max} again favored Caputo (0.184 vs 0.101 cm·min^{-1}), with similar t50 (60.0 vs 56.6 min).

At 20%, Caputo maintained advantages in H_{max} (8.18 ± 0.26 cm vs 6.62 ± 0.49 cm; p = 0.016; d = 3.95) and Rise% (146.3 ± 9.85% vs 125.9 ± 44.4%; p = 0.511; d = 0.64), though it reached t50 later (76.6 vs 53.3 min). Overall, these contrasts indicate that Caputo achieves greater final development and higher peak growth, whereas B-mix tends to rise earlier but to a lower final extent.

Trends within mixes. For Caputo, Rise% followed a shallow dome, peaking at 15% (170.6%) and decreasing at 20% (146.4%); H_{max} also declined with increasing bean-flour replacement, while μ_{max} remained broadly similar (~0.177–0.187 cm·min^{-1}). For B-mix, final-performance metrics (Rise%, H_{max}, μ_{max}) tended to decrease with replacement, although t_{50} remained shorter than Caputo at all levels.

Considering the within-mix extremes, Caputo showed a clear drop in H_{max} from 11.59 ± 1.02 cm at 0% to 8.18 ± 0.26 cm at 20% (Welch t ~ 5.56, df ~ 2.26; p ~ 0.023; mean difference 3.41 cm, 95% CI 0.77–6.04; Cohen's d ~ 4.54, very large), indicating that separation within Caputo is driven primarily by final height rather than timing (μ_{max} 0.181 ± 0.026 vs 0.177 ± 0.063 cm·min^{-1}; t_{50} 70 vs 76.6 min).

In B-mix, H_{max} was lower at 20% than at 0% (7.92 ± 0.62 vs 6.62 ± 0.49 cm); the Welch test yielded t ~ 2.84, df ~ 3.79; p ~ 0.066, with a mean difference of 1.30 cm (95% CI −0.16 to 2.76), and a very large effect size (Cohen's d ~ 2.32;). This documents a sizable reduction between the 0% and 20% conditions, although statistical significance is not achieved at α = 0.05 with triplicates.

Precision and repeatability. Group statistics (Table 5.9) show that the device is precise for the primary endpoint (H_{max}). Across Mix × substitution level (%), H_{max} showed low dispersion (CV < 10 %, with several values in the 2-7 % range), indicating excellent repeatability of the IoT height measurement. The timing variable (t_{50}) was stable within each condition, with absolute SDs of only ~5–15 min and several identical replicate values due to the 10-min sampling step.

Table 5.9. Summary statistics by Mix × substitution level (%): mean ± SD and CV% for H_{max}, μ_{max}, t_{50} and Rise% (n = 3).

Mix	Percent	H_{max} (cm)		μ_{max} (cm/min)		t_{50} (min)		Rise%	
		Mean±SD	CV%	Mean±SD	CV%	Mean±SD	CV%	Mean±SD	CV%
Caputo	0	11.59 ± 1.02	8.87	0.181 ± 0.026	14.74	70 ± 0	0.00	240.7 ± 92.2	38.31
Caputo	10	9.38 ± 0.64	6.91	0.186 ± 0.07	37.88	63.3 ± 20.8	32.87	156.5 ± 24.4	15.58
Caputo	15	9.02 ± 0.06	0.71	0.184 ± 0.033	18.45	60 ± 10	16.67	170.6 ± 16.9	9.96
Caputo	20	8.18 ± 0.26	3.22	0.177 ± 0.063	35.95	76.6 ± 5.7	7.53	146.3 ± 9.8	6.73
B-mix	0	7.92 ± 0.62	7.87	0.174 ± 0.062	35.67	53.3 ± 15.2	28.64	171.5 ± 58.1	33.89
B-mix	10	6.96 ± 0.36	5.17	0.112 ± 0.041	37.42	50 ± 0	0.00	101.7 ± 15.7	15.52
B-mix	15	7.16 ± 0.17	2.42	0.101 ± 0.013	12.83	56.6 ± 15.2	26.96	135.9 ± 48.6	35.81
B-mix	20	6.62 ± 0.49	7.42	0.105 ± 0.019	18.72	53.3 ± 5.7	10.83	125.9 ± 44.4	35.27

As expected for a derivative, μ_{max} exhibited higher CVs (12–38 %), but added discriminatory power on kinetics (notably at 15% substitution). Importantly, the differences in H_{max} between substitution levels were several times larger than the within-level SDs (mean gaps ~1–3 cm vs SD ~0.1–1.0 cm), indicating that the signal clearly exceeds measurement noise. By contrast, Rise (%) tended to be more variable because it is a ratio that depends on both H_0 and H_{max}; when H_0 is small, even small absolute fluctuations translate into larger relative changes, inflating CV_{Rise} (~ 6–38%). This does not call the device into question—H_{max} remains the most robust endpoint—while Rise% may be useful when a normalized expansion metric is needed (e.g., to compare different initial fills or jar geometries). Overall, the device is precise and repeatable for the primary endpoint and yields consistent kinetic descriptors suitable for comparing formulations.

Trends across substitution level. The IoT height signal captured clear formulation effects. Figure 5.8 shows a clear decrease of H_{max} with increasing bean-flour substitution in both mixes. In Caputo, the group mean declines from about 11.6 cm at 0% to about 8.2 cm at 20%, whereas in B-mix it drops from roughly 7.9 cm to 6.6 cm over the same range. These trends confirm that the height-based endpoints captured by the IoT device are responsive to formulation changes.

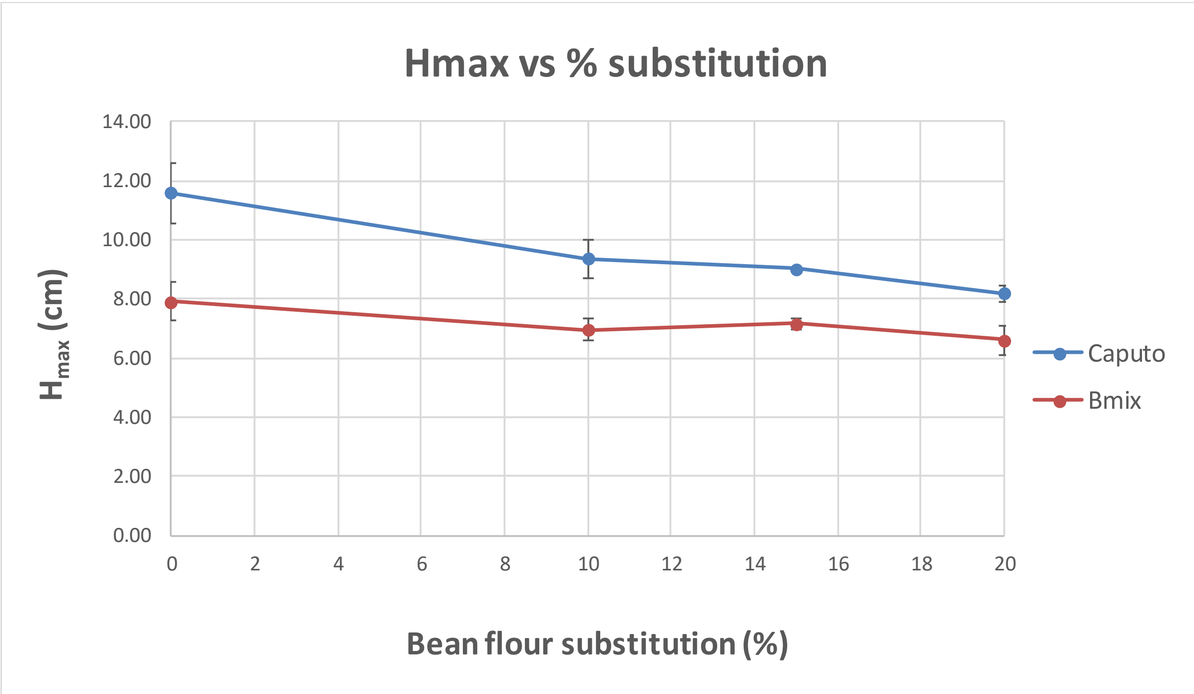

Figure 5.8. Maximum height (H_{max}) vs bean-flour substitution (%) for Caputo and B-mix. Markers show group means (n = 3); error bars are ± SD.

Sensitivity and discrimination. Using only IoT-derived height data, the system clearly differentiated formulations and substitution levels (Figure 5.8). Within Caputo, H_{max} decreased linearly with bean flour replacement (slope −0.168 cm/%, $r = -0.985$, $p = 0.015$), whereas in B-mix the decline was milder (slope −0.060 cm/%, $r = -0.925$, $p = 0.075$). For t_{50} and μ_{max} in Caputo, linear trends were weak ($r \sim 0.15$; $p \approx 0.85$ and $r \sim -0.37$; $p \approx 0.63$, respectively). These trends are sufficient to rank the doughs for subsequent baking trials and to select the most promising base (Caputo gives both higher H_{max} and a stronger sensitivity to substitution).

Kinetic speed (μ_{max}) and timing (t_{50}). The μ_{max} profiles (Figure 5.9) add a complementary view on how the dough rises. Even when absolute height differences (H_{max}) are modest, μ_{max} can still separate conditions by dynamic behavior. In particular, at 15% substitution μ_{max} separates the two mixes strongly (Welch comparison gave $p \sim 0.04$ with a very large Cohen's $d > 3$), indicating different proofing dynamics despite similar end heights. Conversely, as expected for a single time landmark, t_{50} shows smaller and less systematic differences across levels, which is consistent with its lower sensitivity to transient growth features.

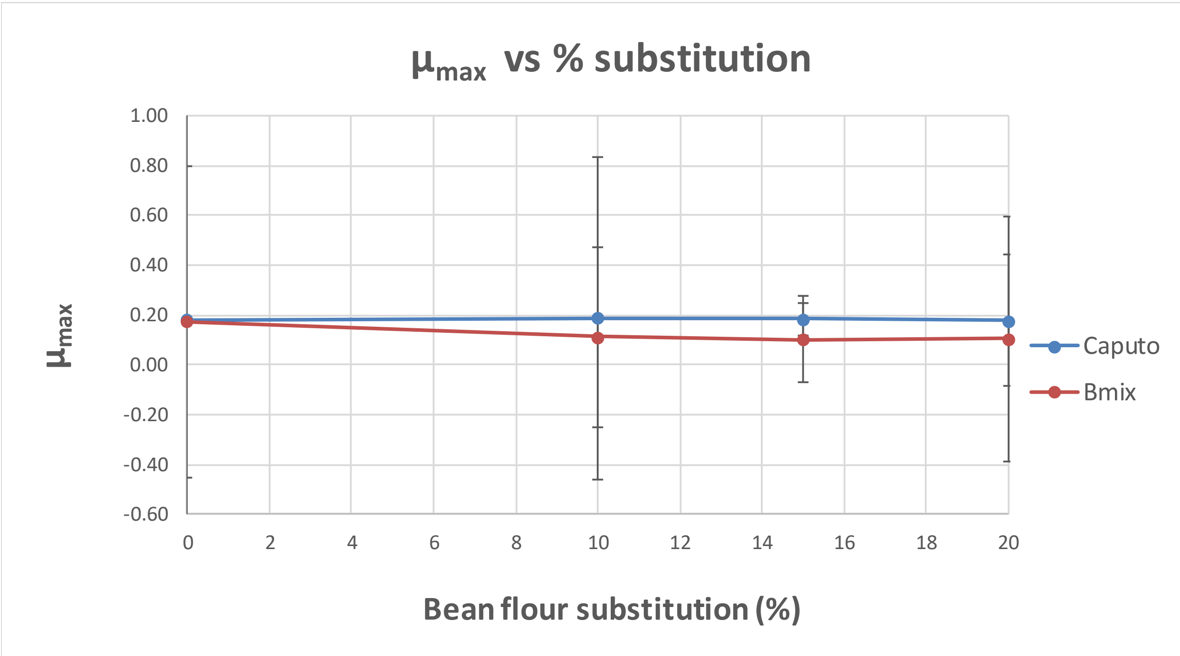

Figure 5.9. Maximum growth rate (μ_{max}) vs substitution level (%) for Caputo and B-mix. Markers show group means (n = 3); error bars are ± SD.

Between-mix discrimination at fixed %. To quantify discrimination at each substitution level Welch's t-tests (two-tailed) were performed comparing Caputo vs B-mix, reporting Cohen's d (pooled SD) to quantify practical relevance. With the small sample size ($n = 3 + 3$), some *p*-values are borderline; however, effect sizes are consistently medium-to-large, especially for μ_{max} (e.g., at 15 % substitution, $p \sim 0.039$, $d > 3$) and for H_{max} at the extremes (Table 5.10). This pattern indicates that—even when formal significance is limited by n—the IoT metrics capture meaningful differences.

Table 5.10. Welch's comparisons (Caputo vs B-mix) at 0, 10, 15 and 20% substitution: two-tailed p-values and Cohen's d for H_{max}, μ_{max} and t_{50}. Medium-to-large |d| values indicate practically relevant separation despite n = 3.

Substitution level %	H_{max} p	H_{max} |d|	μ_{max} p	μ_{max} |d|	t_{50} p	t_{50} |d|
0	**0.010**	4.307	0.866	0.151	0.199	1.543
10	**0.010**	4.609	0.207	1.284	0.383	0.906
15	**0.001**	14.301	**0.039**	3.192	0.770	0.258
20	**0.016**	3.947	0.182	1.527	**0.008**	4.041

μ_{max} as secondary endpoint (growth kinetics). The maximum growth rate (μ_{max}) confirmed the superiority of Caputo at the replacement levels of practical interest. At 0% the two mixes were indistinguishable (0.182 ± 0.027 vs 0.175 ± 0.062 cm·min^{-1}; Welch p = 0.866; d = 0.15). From 10% onward, μ_{max} favored Caputo: at 10% the difference was large though not significant with triplicates (0.187 ± 0.071 vs 0.112 ± 0.042 cm·min^{-1}; p = 0.207; d = 1.28), at 15% it became statistically significant with a very large effect (0.18 ± 0.03 vs 0.10 ± 0.01–0.02 cm·min^{-1}; p = 0.039; d ~ 3.2–3.6), and at 20% the difference remained large but not significant (0.18 ± 0.06–0.07 vs 0.11 ± 0.02 cm·min^{-1}; p = 0.182; d = 1.53).Taken together with H_{max} and Rise%, these kinetics indicate that Caputo not only attains greater final expansion but also sustains higher peak growth at 10–20% bean flour, whereas B-mix tends to rise earlier (shorter t_{50}) but to a lower final extent.

KPI scorecard. To provide an at-a-glance summary, the KPI scorecard reports, for each substitution level, the Welch p -value and |Cohen's d| for H_{max}, μ_{max}, and t_{50} (Table 5.11). Comparisons with small p and large |d| indicate robust separation; H_{max} is strongest at the extremes (0% and 20%), while μ_{max} contributes most at 15%.

Table 5.11. KPI scorecard by substitution level (Caputo vs B-mix; n = 3+3). Evidence classes: Strong = $p < 0.05$ and $|d| \geq 0.8$; Promising = $p \geq 0.05$ with $|d| \geq 0.8$; Weak/Inconclusive = $|d| < 0.8$ regardless of p. Entries are reported as (p; $|d|$).

Substitution level (%)	Hmax	μ_{max}	t_{50}
0	Strong (0.010; 4.31)	Weak (0.866; 0.15)	Promising (0.199; 1.54)
10	Strong (0.010; 4.61)	Promising (0.207; 1.28)	Promising (0.383; 0.91)
15	Strong (0.001; 14.30)	Strong (0.039; 3.19)	Weak (0.770; 0.26)
20	Strong (0.016; 3.95)	Promising (0.182; 1.53)	Strong (0.008; 4.04)

Overall, the IoT device alone provides a coherent kinetic picture with smooth height curves and interpretable KPIs, and both H_{max} and μ_{max} vary with formulation in the expected direction. Discrimination is robust, as H_{max} declines with substitution—more steeply in Caputo—and μ_{max} distinguishes the mixes at specific levels, notably 15 %. Repeatability is adequate for decision-making, with low CVs for H_{max} and stable timing variables, while μ_{max}—despite higher variability—still adds genuine discriminatory power on dough dynamics. The combination of low CVs and medium-to-large Cohen's d values indicates that differences are practically meaningful even when *p*-values are marginal with n=3. Taken together, the monotonic height trends and the large between-mix effect sizes support the practical sensitivity of the IoT measurements. These results show that the IoT device alone, without auxiliary CO_2/O_2/pH, is sufficient to monitor gluten-free dough proofing, summarize kinetics with simple endpoints, and discriminate mixes and substitution levels in a repeatable manner.

Interpretation. The data suggest that Caputo has superior gas retention/structure at all replacement levels, while B-mix ferments faster initially but reaches lower final expansion. The strong and consistent advantage of Caputo in H_{max} indicates better dough rheology and/or compatibility with bean flour. The non-significant results for Rise% at 0%, 15%, and 20% are likely due to limited power (n = 3) and higher variance; nevertheless, the effect sizes ($|d| \sim 0.6$–1.0) remain practically meaningful.

Objective 2

Ambient variability and potential impact. Across the 24 proofing runs, ambient conditions measured by the DHT22 were reasonably stable: temperature ranged from 20.22 to 25.87 °C (mean ~ 23.16 °C) and relative humidity from 90.55 to 102.76 % (mean 97.71 %). Simple linear regressions fitted across all runs showed a modest and non-significant association between H_{max} and temperature (slope 0.31 cm/°C, Pearson's r = 0.345, p = 0.098) and a negligible association with relative humidity (0.078 cm/%RH, Pearson's r = 0.116, p = 0.589). To put these magnitudes in context, temperature spanned ~ 5.65 °C (~ 20.22–25.87 °C); with a slope of 0.31 cm/°C this corresponds to ~ 1.75 cm (0.31 × 5.65). RH spanned ~ 12.21 % (~ 90.55–102.76 %), so—even across the full span—the expected change in H_{max} would be only ~ 0.95 cm (0.078 × 12.21). Both contributions are modest and smaller than the formulation effect (e.g., Caputo 0% vs 20%: 3.41 cm, p = 0.031; B-mix 0% vs 20%: 1.30 cm, p = 0.066), supporting the robustness of the IoT device's height signal with respect to typical T/RH variability. While not dominant, these environmental contributions are non-zero, which motivates a light first-order correction in subsequent analyses.

Adjusted heights (H_{max_adj}). After T/RH adjustment, variability within each Mix × substitution level (%) remained low (Caputo SD ~ 0.31–1.18 cm; B-mix SD ~ 0.77–0.87 cm), corresponding to coefficients of variation of roughly ~ 3-12%, indicating that the correction did not inflate noise (Table 5.12). Here, H_{max_adj} denotes the maximum rise height corrected to the overall mean temperature and relative humidity (~ 23.16 °C and 97.71%) using the fitted T/RH slopes; "mean H_{max_adj}" is the average of these corrected values within each Mix × substitution level. The expected ranking was preserved (Caputo > B-mix at every percentage). Regressing H_{max_adj} on bean-flour substitution showed only a mild, non-significant downward tendency: for Caputo the fitted slope was – 0.117 cm/% (r ~ – 0.83; two-tailed p = 0.173), and for B-mix – 0.019 cm/% (r ~ – 0.48; p = 0.517). Across the four substitution levels (n = 3 per level), SDs were small (~ 0.3–1.2 cm). Taken together, these results indicate that the IoT device provides repeatable height measurements and that the observed differences in leavening are driven primarily by formulation, rather than by fluctuations in ambient temperature or humidity. Thus, the adjustment removes a modest ambient component while retaining differences attributable to mix and substitution level.

Table 5.12. Summary statistics of adjusted maximum height (H_{max_adj}) by Mix × substitution level (%): mean, SD, CV% (n = 3).

Mix	Substitution level (%)	H_{max_adj} (cm)	SD (cm)	CV (%)	Δ vs Hmax cm)
Caputo	0	11.25	1.18	10.50	−0.34
Caputo	10	8.82	0.84	9.57	−0.57
Caputo	15	8.65	0.31	3.61	−0.38
Caputo	20	9.08	0.38	4.16	+0.89
B-mix	0	7.68	0.88	11.40	−0.25
B-mix	10	6.85	0.87	12.66	−0.12
B-mix	15	7.31	0.77	10.58	+0.15
B-mix	20	7.24	0.84	11.59	+0.61

Δ vs Hmax = mean(Hmax_adj) − mean(Hmax) for the same Mix × %.

The adjusted height trends are visualized in Figure 5.10.

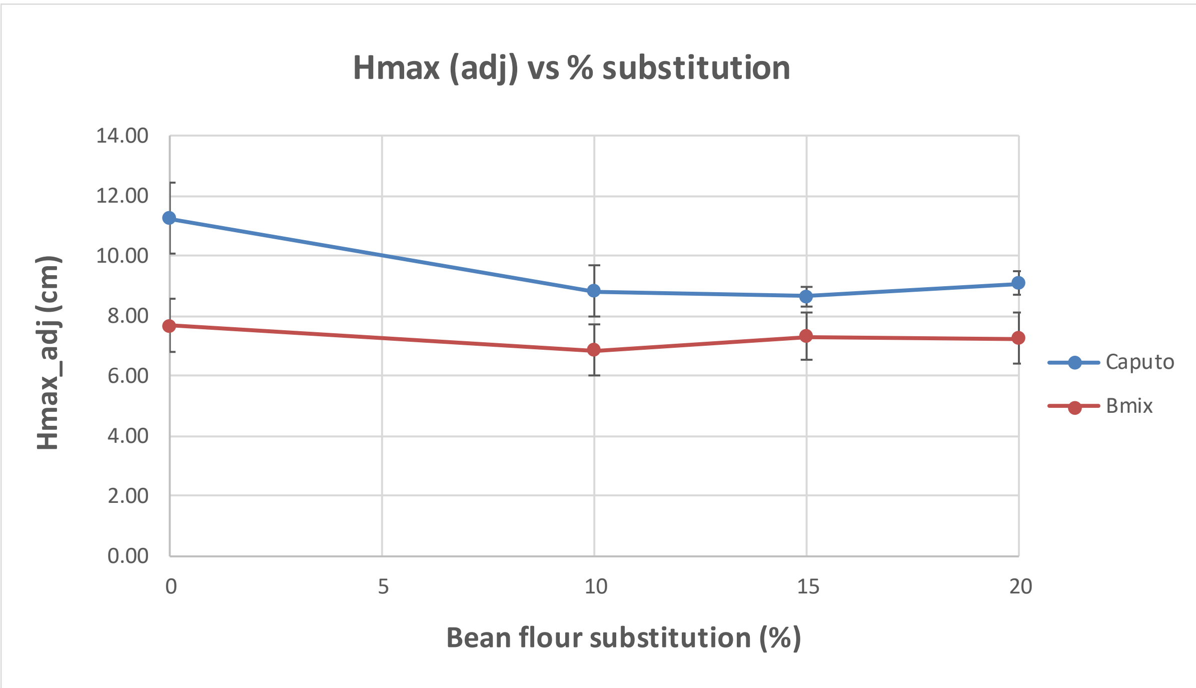

Figure 5.10. Adjusted maximum height (H_{max_adj}) versus bean-flour substitution (%) for Caputo and B-mix. Points are group means (n = 3) with error bars representing ± SD.

Within-mix extreme contrasts (0% vs 20%) on H_{max_adj}. For Caputo, the mean H_{max_adj} was ~ 11.25 cm at 0% and ~ 9.08 cm at 20% (difference 2.17 cm, ~19%). Welch's test did not reach conventional significance with triplicates (t ~ 3.03, df ~ 2.41, p ~ 0.094, two-sided; 95% CI −0.91 to 5.25 cm), but the effect size was very large (Cohen's d ~ 2.47), indicating a substantial practical reduction in peak height. Importantly, this 2.17 cm adjusted drop exceeds the worst-case change expected from the observed temperature span (~1.75 cm) and is much larger than that from relative humidity (~0.95 cm), showing that the device detects formulation-driven differences rather than ambient drift. The very large effect size also indicates high discriminative sensitivity even with n = 3 per group. For B-mix, the mean H_{max_adj} changed little across the extremes (from ~ 7.68 cm to ~ 7.24 cm; difference ~ 0.44 cm, ~6%). This contrast was not significant (t ~ 0.63, df ~ 3.99, p ~ 0.573; 95% CI −1.79 to 2.67 cm), with a small-to-moderate effect size (d ~ 0.51), suggesting that in this mix the true formulation effect on peak height is modest rather than being masked by measurement noise. Taken together, after accounting for temperature and humidity, Caputo still shows a large practical drop in peak height between 0% and 20%, whereas B-mix shows minimal change over the same range.

Composite IoT score (exploratory). A standardized composite score was defined to summarize device-only information after ambient correction: SCORE = $0.5 \cdot z(H_{max\_adj}) + 0.3 \cdot z(\mu_{max}) + 0.2 \cdot z(t_{50\_INV})$. Figure 5.11 summarizes the behavior of the composite score across substitution levels.

Regressed on bean-flour substitution, the SCORE declined for both mixes (Caputo slope −0.0417 SCORE units per %, r = − 0.95, t = − 4.28, p = 0.050; B-mix slope − 0.0281 per %, r = − 0.85, p = 0.151). Caputo consistently showed higher SCORE than B-mix at every percentage, and error bars were small (group SD ~ 0.17–0.54 z-units), confirming good repeatability.

Between-mix comparisons at matched percentages (Welch tests, two-sided) confirmed clear separation: at 0% and 15% the differences were statistically significant (p ~ 0.029 and p ~ 0.037, |d| ~ 1.76 and 1.83), while at 10% and 20% *p*-values were marginal (p ~ 0.073, 0.094) but effects remained large (|d| ~ 1.53, 1.05). At the extremes within each mix (0% vs 20%), Welch contrasts on SCORE were large despite n = 3 per group—Caputo d = 1.81 (t = 2.21, df = 3.66, $p \sim 0.098$) and B-mix d = 1.17 (t = 1.43, df = 3.92, p ~ 0.226)—with 95% confidence intervals that include zero, explaining the nonsignificant *p*-values, yet indicating practically meaningful separation that would likely reach significance with modestly larger samples.

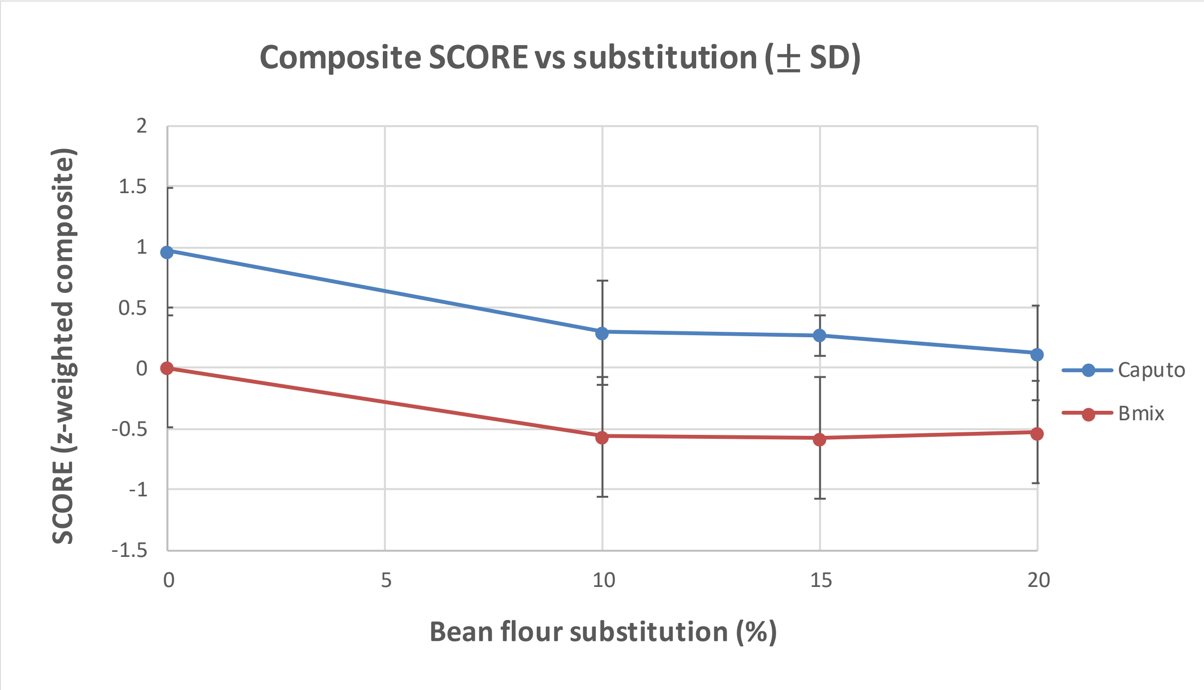

Figure 5.11. Composite IoT score (SCORE = 0.5·z(H_{max_adj}) + 0.3·z(μ_{max}) + 0.2·z(t_{50_INV})) versus bean-flour substitution (%) for Caputo and B-mix. Points are means (n = 3); error bars are ± SD.

Taken together, the composite concentrates the kinetic signal while limiting single-metric noise, preserves the expected ranking (Caputo > B-mix at each level), and remains robust to moderate T/RH variability—all without gas sensors—thereby making the IoT system a stand-alone tool for recipe ranking and monitoring dough leavening.

Interpretation. The T/RH check shows that ambient variability can account for at most ~ 0.95 cm of height shift due to humidity and ~ 1.75 cm due to temperature over the observed ranges. After correcting for these effects, the formulation signal remains dominant: Caputo maintains higher adjusted heights and exhibits a clear downward trend with substitution, whereas B-mix changes are modest. The composite score provides a single, repeatable metric that tracks both final expansion and kinetics; it preserves the same ordering and, in Caputo, reaches borderline trend significance (slope −0.0417 per %, $r = -0.95$, $p = 0.050$) despite the small sample size.

Discussion. The IoT monitoring system delivered reliable, continuous height-time signals with low within-condition variability, allowing quantitative tracking of gluten-free dough proofing. Across substitution levels, formulation effects were clearly detected: maximum height declined with increasing bean-flour replacement, more steeply in Caputo from ~ 11.6 to ~ 8.2 cm and more moderately in B-mix from ~ 7.9 to ~ 6.6 cm. Kinetic behavior was consistent with these trends: Caputo maintained higher peak growth rates (μ_{max}), whereas B-mix typically reached 50% rise earlier (shorter t_{50}) but achieved a lower final expansion. Up to 15% replacement, fermentation kinetics were largely preserved in Caputo (small SDs, stable μ_{max}), while B-mix showed a milder but progressive reduction; at 20% both mixes exhibited a clearer downward shift in final height. These patterns are compatible with the higher fiber content and water-binding properties of legume flour (Tas *et al.*, 2022), which can increase dough consistency and limit gas retention.

Environmental checks confirmed that ambient temperature and RH contributed only modestly to H_{max} variability over the observed ranges; after a light first-order correction, the same rankings and trends were retained. Overall, the device proved suitable for small-scale experimental setups, providing repeatable endpoints (height, rate, timing) that sensitively differentiate mixes and substitution levels in real time.

Concluding remarks. Objective 2 showed that ambient temperature and humidity—measured by the DHT22—had only modest effects on maximum height, and a simple first-order linear correction removed these small biases without inflating variability. After adjustment, trends and rankings were preserved: Caputo remained higher at all levels and showed a clearer decline with substitution, whereas B-mix changed little, confirming that formulation (not climate drift) drives the signal. A standardized composite score combining H_{max_adj}, μ_{max}, and t_{50} further concentrated discrimination while retaining repeatability. In short, the environmental check validates the device: the conclusions from Objective 1 hold on climate-adjusted endpoints, and a single, climate-robust indicator is available when desired. Altogether, the IoT platform—without auxiliary CO_2/O_2/pH sensors—provides repeatable kinetic measurements, discriminates mixes and substitution levels, and offers a practical one-number readout for recipe ranking and process control in gluten-free doughs.

Auxiliary sensors and environment: data audit and correlation with IoT endpoints.

CO_2, O_2 and pH from the companion jars, together with local temperatures from four K-type probes, were logged throughout proofing. Before the device-only analysis, these auxiliary signals were audited across the 24 runs and compared with the height-derived endpoints from the IoT devices (H_{max}, μ_{max}, t_{50}) using Pearson correlations and simple linear regressions. Analyses were performed both (i) across runs and (ii) on within-condition residuals (after removing the Mix × substitution level % mean) to reduce confounding by formulation. Auxiliary variables varied within narrow–moderate ranges (Table 5.13).

Table 5.13. Descriptive ranges (min–max, mean, SD) for pH, CO_2, O_2, K-probe temperature, and DHT22 T/RH across the 24 runs.

Variable	Min	Max	Mean	SD
pH	5.21	5.90	5.51	0.17
CO_2 (%)	0.00	2.08	0.77	0.64
O_2 (%)	18.71	20.43	19.87	0.52
K-probe temperature (°C)	23.00	27.90	25.23	1.66
DHT22 temperature (°C)	19.71	26.38	23.02	1.77
DHT22 RH (%)	90.55	102.76	97.71	2.41

pH, CO_2, O_2 and K-probe temperature are per-replicate means over the proofing run.
DHT22 values are ambient means.

Across runs, H_{max} showed a strong inverse association with pH ($r = -0.673$, $p < 0.001$), while other links were small-to-moderate (e.g., H_{max} vs O_2 $r = 0.374$, $p = 0.071$; H_{max} vs device temperature $r = 0.347$, $p = 0.097$). μ_{max} correlations were generally weak and non-significant. For timing, t_{50} correlated moderately with O_2 ($r = 0.426$, $p = 0.037$) and was borderline with CO_2 ($r = -0.395$, $p = 0.055$). When confounding by formulation and ambient DHT22 readings was removed (within-condition residuals), associations with H_{max} and μ_{max} became weak and non-significant (e.g., H_{max} vs device temperature $r = 0.366$, $p = 0.078$), whereas t_{50} retained the expected moderate links to pH, CO_2 and O_2 ($r = 0.553/-0.522/0.527$; all $p \leq 0.009$), consistent with shared tracking of fermentation progress. K-probe temperatures closely followed the DHT22 trend and were largely redundant (Tables 5.14-5.15).

Table 5.14. Pearson r (with two-sided p) between each auxiliary variable and H_{max}, μ_{max}, t_{50} (cross-run correlation).

Endpoint	pH	CO2 (%)	O2 (%)	$T_{K\text{-type}}$	T_{Device}	RH_{Device}
H_{max}	**−0.673 (p=0.001)**	−0.256 (p=0.229)	0.374 (p=0.071)	0.005 (p=0.980)	0.347 (p=0.097)	0.039 (p=0.859)
μ_{max}	−0.067 (p=0.757)	0.294 (p=0.164)	−0.265 (p=0.211)	−0.144 (p=0.489)	−0.054 (p=0.803)	0.036 (p=0.870)
t_{50}	0.246 (p=0.246)	−0.395 (p=0.055)	**0.426 (p=0.037)**	−0.368 (p=0.076)	−0.218 (p=0.305)	0.213 (p=0.317)

Table 5.15. Within-condition (Mix × substitution level %) residual correlations.

Endpoint	pH	CO2 (%)	O2 (%)	$T_{K\text{-type}}$	T_{Device}	RH_{Device}
H_{max}	0.084 (p=0.704)	−0.210 (p=0.323)	0.299 (p=0.158)	−0.300 (p=0.156)	0.366 (p=0.078)	−0.169 (p=0.425)
μ_{max}	−0.156 (p=0.463)	0.159 (p=0.453)	−0.242 (p=0.255)	−0.121 (p=0.571)	−0.086 (p=0.694)	−0.063 (p=0.772)
t_{50}	**0.553 (p=0.005)**	**−0.522 (p=0.009)**	**0.527 (p=0.008)**	−0.350 (p=0.094)	−0.063 (p=0.775)	0.201 (p=0.344)

Adding pH, CO_2, O_2 and K-probe temperatures as covariates (in addition to Mix × substitution level % and DHT22 T/RH) did not alter substitution-level trends or Caputo vs B-mix contrasts for H_{max} and μ_{max}: slope magnitudes and signs remained stable, p-values stayed in the same interpretive bands, and improvements in model fit were negligible. This aligns with the residual-correlation analysis (Table 5.15), where auxiliary variables showed weak, non-significant links to H_{max} and μ_{max} after removing formulation effects; only t_{50} retained modest associations with pH, CO_2, and O_2, consistent with shared fermentation timing. Consequently, the main results focus on the height-derived IoT endpoints, using gas, pH, and K-probe data as contextual quality checks rather than primary predictors.

Gluten-free Bread Quality

Introduction

Gluten-free bread (GFB) remains one of the most technologically challenging products within the gluten-free bakery category. In conventional wheat systems, gluten proteins develop a viscoelastic network capable of retaining gas during fermentation and baking, thereby underpinning loaf volume, crumb structure, elasticity, and overall palatability. In the absence of gluten, gluten-free doughs (GFDs) behave more like high-hydration batters, with limited gas-holding capacity and weak structure, which commonly leads to reduced specific volume, coarse or fragile crumb, rapid staling, and suboptimal sensory attributes (e.g., dryness, crumbliness). Beyond texture, the nutritional quality of many starch-based GFB formulations is often limited, with relatively low protein and fiber contents and a tendency toward higher glycemic responses. A broad range of structuring strategies has been explored to overcome these limitations, including the use of hydrocolloids (e.g., psyllium, HPMC), emulsifiers, enzymes, proteins from non-gluten sources, and tailored starch blends. While these approaches can partially mimic gluten functionality, they may introduce cost or labelling constraints and not always deliver robust performance across formulations and processes. In parallel, legume flours have attracted growing interest as multi-functional ingredients that can simultaneously contribute proteins, soluble and insoluble dietary fiber, and bioactive compounds, potentially improving water-binding, gelation, and film-forming properties in gluten-free matrices and enhancing the nutritional profile of the final bread. However, the incorporation of legume flours into GFB also poses challenges, including potential beany notes, darker color, and the presence of seed-coat components that can interfere with dough rheology. Dehulling and appropriate milling are recognized pretreatments to mitigate some of these issues by eliminating seed coats, which may attenuate off-flavors and modify water uptake, with positive repercussions on crumb structure. Within this framework, locally adapted ecotypes represent a promising avenue to couple technological performance with territorial identity and sustainability.

This chapter investigates the use of dehulled bean flours (DBFs) obtained from two local ecotypes under the PGI “Fagioli di Sarconi”—Tabacchino and Verdolino—as partial replacements for a commercial gluten-free flour mix (Caputo). Building on the leavening trials conducted previously in this work, the Caputo mix was selected as the operational baseline. Treatments consisted of 10% and 20% flour substitution levels for each ecotype, alongside a Caputo-based control. All baking tests were carried out at LAQV-REQUIMTE — Associated Laboratory for Green Chemistry, ESS|P.PORTO (Porto, Portugal) during the research period abroad. The study evaluates the technological and compositional attributes actually measured during the trials—namely specific volume, color of crust and crumb, moisture, protein, fat, ash, and mineral elements—as indicators relevant to product quality and shelf life. Beyond improving the nutritional quality of GFB, a key motivation of this study is the valorization of non-compliant beans that fail to meet the aesthetic specifications of the IGP supply chain. By dehulling and milling these otherwise downgraded lots into functional flours for gluten-free breadmaking, the approach aimed to upcycle a local by-product stream, support growers' revenues, and advance circular-economy goals without compromising technological performance.

Materials and Methods

Formulation and sample coding

Five bread formulations were tested (Table 5.16), using the Caputo gluten-free flour mix as constant matrix, with DBFs from local PGI "Fagioli di Sarconi" ecotypes, "Tabacchino" and "Verdolino". All trials were performed in triplicate.

Table 5.16. Experimental codes for the GFB formulations: PGI "Fagioli di Sarconi" ecotypes and substitution levels (% w/w) of DBF in a Caputo-based formulation.

Code	Ecotype	Substitution (% w/w)
A	-	-
B	Tabacchino	10
C	Tabacchino	20
D	Verdolino	10
E	Verdolino	20

A = Control; B = TAB10%; C = TAB20%; D = VER10%; E = VER20%.

Composition and preparation of experimental of GFBs

GFBs were prepared using a commercial gluten-free baking mix as the base, with partial substitution by DBF. Two substitution levels were tested: 10% and 20% (w/w), replacing an equivalent proportion of the commercial mix. A control dough containing only the commercial mix, without bean flour, was also prepared.

The control formulation had been optimized in preliminary trials and served as the reference recipe for all experiments. The base formulation consisted of a GF flour mix (Caputo Fioreglut), Nutrifree wholemeal bread mix (NT Food S.p.A., Italy), fresh yeast (Levanova, Spain), salt (Saldomar, Portugal), extra virgin olive oil (Oliveira da Serra Selection Ouro, Portugal), and tap water. DBF was incorporated into the experimental formulation as a substitute for the flour mixes (Table 5.17). Ingredients proportions were standardized across all trials to ensure comparability of results.

Table 5.17. Composition of experimental GFBs.

Ingredient (%)	Control	DBF10%	DBF20%
Caputo gluten-free flour mix	34.0	30.6	27.2
Whole meal bread flour mix	17.0	15.3	13.6
Fresh yeast	1.0	1.0	1.0
Salt	0.5	0.5	0.5
Extra virgin olive oil	1.7	1.7	1.7
DBF	-	5.1	10.2
Water	45.8	45.8	45.8

A straight-dough method was used to prepare the experimental GFDs. Given the small batch size, mixing was performed in a stainless-steel bowl with a spoon at room temperature (23 ± 1 °C). The flours were first homogenized (dry blending). Yeast, previously dissolved in water tempered to 30 ± 2 °C to ensure even distribution, was then added, followed by oil and salt. Mixing continued until a smooth, uniform batter was obtained, with no visible lumps or unincorporated particles. Doughs were proofed in the mixing bowls covered with a clean kitchen towel for 2 hours at ~23 °C. After proofing, each bowl was inverted to release the dough directly onto an inverted baking sheet lined with floured parchment paper, and the loaf was gently shaped with lightly oiled hands to minimize degassing. Samples were baked on the lower rack of a preheated conventional oven (Teka, Germany) for 15 min at 220 °C, then for 35 min at 200 °C. Baked loaves were cooled for 2 h at room temperature before further analyses.

Samples preparation for further analysis

Fresh GFB samples were used to determine moisture content and physical parameters. In contrast, freeze-dried GFB samples were used for the determination of proximate chemical composition and mineral and trace element content.

Briefly, one whole loaf from each formulation was manually crushed, packed in a paper envelope, and placed in an ultra-low-temperature freezer at -80 °C for at least 24 h. The frozen samples were then placed in a freeze-dryer (Labconco Corporation, Kansas City MO, USA) for approximatively 40 h. The freeze-dried material was ground with a stainless-steel mill (Thermomix Vorwerk TM6, Wuppertal, Germany) for 15 s and sieved through a 0.40-mm mesh. The resulting homogeneous powder was packed in sealed polyurethane bags and stored at 4°C in the dark until analysis.

Characteristics of experimental gluten-free breads

Analysis of nutritional composition

Moisture was determined according to AOAC Official Method 925.10. Approximatively 2 ± 0.01 g of freshly baked gluten-free bread (2 h after baking), finely crumbled and homogenized, were weighed into pre-dried, tared glass crucibles with lids using an analytical balance (±1 mg). The open crucibles (lids placed underneath) were dried for 1 h at 130 °C ± 3 °C in a forced-air drying oven, then immediately covered, cooled to room temperature in a desiccator, and reweighed. Moisture content (%) was calculated from the mass loss on drying (Equation 7):

$$Moisture\ (\%) = \frac{m_1 - m_2}{m_1 - m_0} \times 100 \tag{7}$$

where m_0 is the mass of the empty crucible with lid, m_1 the mass of crucible with the sample before drying, and m_2 after drying. Results were reported on a wet basis. All measurements were performed in triplicate.

Protein content was determined in accordance with the copper-catalyst Kjeldahl method (AOAC 984.13). Approximately 1.000 ± 0.001 of freeze-dried GFB samples was weighed into a Kjeldahl digestion flask using an analytical balance (±1 mg). Samples were digested with concentrated H_2SO_4 and copper catalyst (with K_2SO_4), then steam-distilled and titrated using a Kjeltec™ 8400 (FOSS, Denmark). Nitrogen content reported by the instrument was converted to crude protein using a nitrogen-to-protein factor (F) according to Equation (8):

$$Protein\ (\%) = N\ (\%) \times F \tag{8}$$

Unless otherwise specified, F = 6.25. Results are expressed on a dry-matter basis. Analyses were performed in triplicate.

Fat content was determined according with PN-ISO 6492:2005. Approximatively 1.000 ± 0.001 g of freeze-dried GFB samples were weighed into a porous cellulose extraction thimble using an analytical balance (±1 mg). The loaded thimble was dried in a forced-air oven at 90 °C for 1 h, cooled to room temperature in a desiccator, and placed in the Soxhlet extractor. A clean, dry 150 mL round-bottom flask was tared, ~90 mL of petroleum ether was added, and the extraction unit was assembled on a heating mantle. The solvent was brought to gentle reflux, adjusting the heat to achieve ~4–6 siphon cycles per hour (≈2–3 drops s^{-1}). Extraction continued for ~6 h. After extraction, the condenser and extractor were removed, the solvent was evaporated, and the flask was dried in an oven at 60–80 °C for 1 h (or to constant mass). The flask was cooled in a desiccator and weighed. Fat content (%) was calculated as (Equation 9):

$$Fat\ (\%) = \frac{m_2 - m_1}{m_s} \times 100 \tag{9}$$

where m_1 is the mass of the empty, dried flask, m_2 the mass of the flask with extracted fat after drying, and m_s the mass of the sample.

Total ash content was determined in accordance with AOAC Official Method 923.03. Porcelain crucibles were pre-ignited in a muffle furnace at 550 °C, cooled to room temperature in a desiccator, and tared. Approximately 2.500 ± 0.001 g of freeze-dried GFB sample was weighed into each crucible using an analytical balance (±1 mg). Samples were ashed at 550 ± 25 °C until light grey/white (≈4–6 h) or to constant mass. Crucibles were cooled in a desiccator and weighed. If mass constancy was not achieved, ignition and cooling were repeated. Ash content (%) was calculated as (Equation 10):

$$Ash\ (\%) = \frac{m_2 - m_0}{m_1 - m_0} \times 100 \tag{10}$$

where m_0 is the mass of the empty crucible, m_1 the mass of the crucible with the sample before ashing, and m_2 after ashing. Results are reported on a dry-matter basis; measurements were run in triplicate.

Determination of physical parameters

The loaf weight was determined using a digital balance (0.01 g accuracy) and its volume was determined using the standard rapeseed displacement method (AACC Approved Methods of Analysis. Method 10-05.01). Three loaves per formulation were analyzed.

Specific volume (SV) was calculated as loaf volume divided by loaf weight and expressed in cm^3/g (equivalently, mL/g). Density (D) was calculated as loaf weight divided by loaf volume and expressed in g/cm^3.

Bake loss (%) was calculated thought Equation (11):

$$Bake\ loss\ (\%) = \frac{(a-b\ ) \times 100}{a} \tag{11}$$

where a is the dough weight (g) and b is the weight of baked and cooled GFB (g).

The height-to-width ratio (H/W) was measured on the central slice of each loaf; height and width were measured in centimeters (cm), and the H/W ratio is dimensionless.

Instrumental color determination

Color was analyzed for the crust surface, the crumb samples at the midpoint of a 20-mm-thick central slice, and the breadcrumb using a Hunter Lab ColorFlex 45/0

(Hunter Associates Laboratory, Inc., Reston, VA, USA). The results were expressed following the CIELab system: lightness L* (= 0 to black; = 100 to white) and chromatic components a* (– a to greenness; + a to redness) and b* (– b to blueness; + b to yellowness). The color values for each kind of GFB were the mean of five replications.

Evaluation of mineral and trace element content

Sample pre-treatment

For total mineral content analysis, GFB samples were solubilized by microwave-assisted acid digestion (ETHOS™ EASY Advanced Microwave Digestion System, Milestone Connect, Sorisole, Italy), adapting the method previously described by Pinto et al. (2016). Approximately 0.8 g of each GFB samples was weighted directly into a polytetrafluoroethylene (PTFE) microwave closed-vessel, then 9 mL of 65% (w/w) HNO_3 and 1 mL of 30% (v/v) H_2O_2 were added. The microwave program was: ramp to 210 ºC over 20 min at 1800 w, hold 15 min at 210 ºC (1800 w), then cool 20 min. After cooling, digests were quantitatively transferred and diluted to 50 mL with ultrapure water in decontaminated volumetric flasks. Reagent blanks were prepared using the same procedure. Each GFB type was digested in triplicate.

Sample treatment

Inductively coupled plasma mass spectrometry (ICP-MS) and flame atomic absorption spectrometry (FAAS) were used to analyze the mineral content in sample solutions obtained from microwave-assisted acid digestion.

ICP-MS and FAAS are both analytical techniques used to determine the elemental composition of a sample. ICP-MS involves the use of argon plasma to dry the liquid samples (called "aerosol" after being nebulized), dissociate the molecules, and finally to remove an electron from the elements, thereby forming singly-charged ions. The ions in the plasma are then directed to a mass spectrometer, where they will be separated by their mass-to-charge ratio. Upon exiting the mass spectrometer, ions arrive at the detector, where they produce a signal that can be used to quantify the concentration of an element in the sample (Wilschefski and Baxter, 2019). In FAAS, the sample is atomized in a flame and the atoms absorb light at characteristic wavelengths. Then, by measuring the reduction in the intensity of the transmitted light, the concentration of the target element can be quantified (Tsalev, 2011).

Although FAAS instruments are typically used for atomic absorption spectroscopy (AAS), in this study, FAAS was employed to perform atomic emission analysis, which involves the measurement of emitted light from excited atoms, providing similar analytical capabilities.

For Na and K, an AAnalyst™ 200 FAAS instrument (PerkinElmer, Überlingen, Germany) was used. For Mg, P, Ca, Mn, Fe, Co, Cu, Zn, and Mo, an iCAP™ Q ICP-MS instrument (Thermo Fisher Scientific, Bremen, Germany) was used. Results are expressed in mg/g dry weight for Na, Mg, P, K, Ca, and as µg/g dry weight for Mn, Fe, Co, Cu, Zn, and Mo; values <LOD are indicated as such.

Statistical analysis

Results are expressed as mean ± standard deviation (SD). Unless noted otherwise, data represent three independent loaves per formulation ($n = 3$); exceptions (e.g., multiple color readings per loaf and the extended H/W measurements) follow the replication scheme specified in the Methods. Differences among formulations (A–E) were tested by one-way ANOVA (Single Factor). When the omnibus F-test was significant ($p \leq 0.05$), Tukey–Kramer HSD was used for pairwise comparisons and outcomes are reported with a compact letter display (means sharing a letter do not differ at $\alpha = 0.05$). ANOVA assumptions (approximate normality of residuals and homogeneity of variances) were checked from residual plots and group-variance summaries; given the small n, diagnostics were primarily graphical. For mineral elements, each analyte was analyzed separately by one-way ANOVA followed by Tukey HSD; where multiple analytes were considered together, the Benjamini–Hochberg false-discovery rate ($q = 0.05$) was additionally reviewed to contextualize multiplicity.

All statistical analyses were conducted in Microsoft Excel (Analysis ToolPak; XLSTAT add-in for post-hoc and multiple-testing utilities).

Results and Discussion

Proximate composition and energy (Table 5.18). Moisture at slicing was tightly clustered across all breads (~41.3–41.5%), indicating comparable bake-out and cooling among batches. On a dry-matter basis, protein increased with the level of dehulled bean flour (DBF) for both ecotypes: from the control (A) 1.40 ± 0.20 g/100 g DM to 3.38 ± 0.22 and 3.00 ± 0.62 at 10% substitution (B, Tabacchino; D, Verdolino), which did not differ from each other, and up to 5.84 ± 0.62 (C, Tabacchino 20%) and 4.50 ± 0.66 (E, Verdolino 20%) at 20%, with Tabacchino 20% > Verdolino 20%. Fat rose only at the higher level (A 1.40 ± 0.15, C 1.92 ± 0.37, E 2.18 ± 0.12 g/100 g DM), while ash showed a clear dose-response (A 1.77 ± 0.04 → ~2.30–2.32 at 20%). As a consequence, carbohydrates by difference decreased with DBF (A 95.43 ± 0.32, C 89.94 ± 0.90, E 90.99 ± 0.68 g/100 g DM).

Table 5.18. Nutritional composition and energy value of experimental GBFs.

	CONTROL A	TAB10% B	TAB20% C	VER10% D	VER20% E
Moisture (%)	41.33 ± 0.40^{a}	41.50 ± 0.52^{a}	41.52 ± 0.38^{a}	41.43 ± 0.49^{a}	41.52 ± 0.42^{a}
Protein (g/100 DM)	1.40 ± 0.20^{a}	3.38 ± 0.22^{b}	5.84 ± 0.62^{c}	3.00 ± 0.62^{b}	4.50 ± 0.66^{d}
Fat (g/100 DM)	1.40 ± 0.15^{a}	1.64 ± 0.27^{a}	1.92 ± 0.37^{b}	1.70 ± 0.18^{a}	2.18 ± 0.12^{b}
Ash (g/100 DM)	1.77 ± 0.04^{a}	2.00 ± 0.05^{b}	2.30 ± 0.08^{c}	2.04 ± 0.06^{b}	2.32 ± 0.07^{c}
Carbohydrates (g/100 DM)	95.43 ± 0.32^{a}	92.99 ± 0.41^{b}	89.94 ± 0.90^{c}	93.25 ± 0.45^{b}	90.99 ± 0.68^{d}
Energy value (kj)	1673 ± 3^{a}	1674 ± 5^{a}	1675 ± 9^{a}	1675 ± 3^{a}	1680 ± 3^{a}
Energy value (kCal)	400 ± 1^{a}	400 ± 1^{a}	400 ± 2^{a}	400 ± 1^{a}	403 ± 1^{a}

DM–Dry Matter. Value with the same letter (a, b, c, d) in each row do not differ significantly (p ≤ 0.05)

Carbohydrates were calculated by difference and therefore include dietary fiber; energy was estimated with Atwater 4–9–4 applied to total carbohydrate, so values may be slightly overestimated (~2 kcal for each gram of fiber not subtracted). Despite the macronutrient shifts, energy remained essentially stable among formulations (~1673–1680 kJ/100 g DM; ~400–402 kcal/100 g DM), reflecting compensatory changes between protein/ash gains and carbohydrate reductions. Overall, DBF addition enhanced protein and mineral (ash) contents in a level-dependent manner; ecotype effects on protein emerged only at 20% (Tabacchino > Verdolino), while moisture and energy were unaffected.

Physical parameters and GFB color

The physical parameters and crust, crumb, and breadcrumb color are presented in Table 5.19.

Physical properties. Specific volume (SV), density, bake loss, and loaf shape (H/W) did not differ significantly among formulations. Specific volume showed a non-significant downward trend with DBF level (A: 2.53 ± 0.12 mL/g; C: 2.11 ± 0.21 mL/g; E: 1.93 ± 0.31 mL/g), mirrored by a reciprocal increase in density (A: 0.40 ± 0.02 g/cm^3; E: 0.53 ± 0.09 g/cm^3). Bake loss ranged from 16.5 to 18.6% with no statistical separation, indicating comparable oven spring and water loss across batches. Likewise, the H/W ratio clustered narrowly (~ 0.36–0.40), supporting the absence of treatment effects on loaf geometry. Overall, within the explored inclusion range (10–20% DBF), dehulled bean flours did not penalize the main technological indicators of loaf structure.

Color (CIELAB)

Crust. Lightness (L*) decreased at the 20% substitution level: both Tabacchino 20% (C) and Verdolino 20% (E) had darker crusts than the control and the 10% breads, while A, B, and D remained comparable. Redness (a*) increased with DBF, with clear rises in B, C, and E; D showed intermediate values. No significant differences were detected for crust yellowness (b*). These results indicate a dose-dependent darkening and reddening of the crust at the 20% level, with a milder response at 10%.

Crumb. DBF addition made the crumb lighter than the control (A 53.83 ± 1.23 L* vs ~56.8–58.3 L* for DBF breads). The a* coordinate shifted slightly toward green only in Verdolino 20% (E), whereas B/C/D were close to the control. Yellowness (b*) increased for Tabacchino 10% (B); C/E were intermediate, and A/D were the lowest. Overall, DBF produced a lighter, slightly more yellow crumb, with modest ecotype/level nuances.

Table 5.19. Physical parameters and color of experimental GBFs.

	CONTROL A	TAB10% B	TAB20% C	VER10% D	VER20% E
Specific volume (mL/g)	2.53 ± 0.12^{a}	2.26 ± 0.18^{a}	2.11 ± 0.21^{a}	2.12 ± 0.24^{a}	1.93 ± 0.31^{a}
Density (g/cm³)	0.40 ± 0.02^{a}	0.44 ± 0.04^{a}	0.48 ± 0.05 ^{a}	0.48 ± 0.06^{a}	0.53 ± 0.09^{a}
Bake loss (%)	18.61 ± 0.42^{a}	17.67 ± 0.59^{a}	16.96 ± 0.53 ^{a}	16.53 ± 1.06^{a}	17.42 ± 1.03^{a}
H/W ratio (–)	0.396 ± 0.05^{a}	0.376 ± 0.03^{a}	0.362 ± 0.02^{a}	0.394 ± 0.03^{a}	0.394 ± 0.02^{a}
Bread crust					
L*	55.25 ± 2.93^{a}	53.91 ± 4.80^{a}	48.46 ± 1.45^{b}	58.52 ± 2.80^{a}	45.02 ± 5.31^{b}
a*	6.04 ± 1.03^{a}	10.97 ± 4.31^{b}	11.58 ± 1.10^{b}	8.04 ± 0.59^{ab}	11.44 ± 2.17^{b}
b*	23.91 ± 0.99^{a}	24.16 ± 2.41^{a}	23.14 ± 2.42^{a}	24.75 ± 1.37^{a}	23.70 ± 3.40^{a}
Bread crumb					
L*	53.83 ± 1.23^{a}	58.10 ± 1.74^{b}	58.29 ± 2.03^{b}	56.93 ± 1.57^{b}	56.77 ± 2.44^{b}
a*	-0.24 ± 0.21^{a}	-0.54 ± 0.11^{ab}	-0.41 ± 0.20^{ab}	-0.41 ± 0.26^{ab}	-0.70 ± 0.15^{b}
b*	5.42 ± 0.64^{a}	7.45 ± 0.67^{b}	6.45 ± 0.77^{ab}	5.32 ± 0.70^{a}	6.24 ± 1.42^{ab}
Breadcrumb					
L*	53.50 ± 0.94^{a}	50.91 ± 0.67^{b}	48.22 ± 0.66^{c}	49.87 ± 1.07^{b}	46.34 ± 1.89^{c}
a*	1.68 ± 0.25^{a}	2.96 ± 0.46^{ab}	4.86 ± 0.74^{b}	3.15 ± 0.56^{ab}	6.94 ± 2.27^{c}
b*	15.66 ± 1.31^{a}	17.67 ± 0.75^{ab}	16.55 ± 2.21^{ab}	16.74 ± 0.88^{ab}	19.03 ± 1.89^{b}

Breadcrumb. Lightness (L*) decreased progressively with substitution (control highest; 10% intermediate; 20% lowest), confirming a darker breadcrumb as DBF increased. Redness (a*) increased with DBF substitution: the control showed the lowest a* values, Tabacchino 20% was higher, and Verdolino 20% was the highest; the

10% breads lay in between. Yellowness (b*) increased notably for Verdolino 20% (E), while changes in the other breads were small to moderate. The breadcrumb therefore captures a clear color gradient with DBF level, more pronounced than in the crumb.

DBFs affected color more than structure: crumb became lighter (vs. control), whereas crust and breadcrumb darkened at 20%, with higher redness—patterns consistent with legume-driven reactions during baking (Maillard precursors, mineral catalysis) and with the pigment profile of the flours. In contrast, SV, density, bake loss and H/W were statistically stable, indicating that the chosen substitution levels allow nutritional enrichment without compromising loaf technology.

Minerals and trace elements

Macrominerals (mg/g dry weight). Sodium (Na) remained essentially stable across breads (~6.0–6.6 mg/g), consistent with the constant salt level in the recipe. By contrast, magnesium (Mg), phosphorus (P), and potassium (K) increased clearly with the level of DBF for both ecotypes. On average, K rose from 0.976 (A) to ~2.63–2.65 at 10% (B/D) and to ~4.03–4.07 at 20% (C/E); P increased from 0.722 (A) to ~1.09–1.13 (10%) and ~1.38–1.44 (20%); Mg from 0.243 (A) to ~0.37–0.39 (10%) and ~0.46–0.50 (20%). Calcium (Ca) showed a more moderate rise (from 0.161 to ~0.19–0.23).

Table 5.20. Macromineral content (mg/g dw) of experimental GFBs.

Macromineral (mg/g dw)	CONTROL A	TAB10% B	TAB20% C	VER10% D	VER20% E
Na	6.209 ± 0.227^{a}	6.308 ± 0.262^{a}	6.003 ± 0.178^{a}	6.573 ± 0.156^{a}	6.444 ± 0.508^{a}
Mg	0.243 ± 0.010^{a}	0.368 ± 0.016^{b}	0.462 ± 0.013^{c}	0.386 ± 0.010^{b}	0.497 ± 0.025^{c}
P	0.722 ± 0.012^{a}	1.130 ± 0.035^{b}	1.440 ± 0.034^{c}	1.091 ± 0.032^{b}	1.377 ± 0.060^{c}
K	0.976 ± 0.065^{a}	2.630 ± 0.170^{b}	4.072 ± 0.166^{c}	2.645 ± 0.048^{b}	4.032 ± 0.290^{c}
Ca	0.161 ± 0.006^{a}	0.193 ± 0.006^{bc}	0.210 ± 0.006^{b}	0.192 ± 0.006^{c}	0.232 ± 0.008^{d}

Values are mean ± SD (n = 3) on a dry-weight basis. Within a row, means sharing a superscript letter do not differ significantly (one-way ANOVA; Tukey HSD, α = 0.05).

Statistically, versus the control (A), Mg, P, K, and Ca were higher in all DBF formulations, whereas Na did not change significantly. At the same substitution level, ecotype differences were limited: at 10%, Tabacchino and Verdolino were essentially overlapping; at 20%, some divergence appeared for Ca, while K, P, and Mg remained similar between C and E.

Trace elements (µg/g dry weight). DBF enrichment markedly increased manganese (Mn), iron (Fe), zinc (Zn), and copper (Cu) relative to the control. For example, Fe rose from 7.54 (A) to ~15.45–13.96 (10%) and ~21.41–19.14 (20%); Zn from 3.23 (A) to ~6.23–5.84 (10%) and ~8.51–8.25 (20%); Mn from 3.51 (A) to ~5.19–4.97 (10%) and ~6.34–6.53 (20%); Cu from 0.54 (A) to ~1.52–1.54 (10%) and ~2.29–2.42 (20%). These increases were significant versus the control for all four elements. Cobalt (Co) increased only slightly (on the order of hundredths of µg/g): differences versus A were present in most contrasts, but B vs D did not separate at 10%. Molybdenum (Mo) was not detected in the control and appeared in DBF breads, with mean levels ~0.42–0.52 (10%) and ~0.72–0.88 (20%); its absence in the control prevents a direct statistical comparison A vs (B–E), but the presence effect is evident.

Table 5.21. Trace element content (µg/g dw) of experimental GFBs.

Trace element (µg/g dw)	CONTROL A	TAB10% B	TAB20% C	VER10% D	VER20% E
Mn	3.513 ± 0.064^{a}	5.189 ± 0.202^{b}	6.336 ± 0.260^{c}	4.973 ± 0.140^{b}	6.529 ± 0.304^{c}
Fe	7.541 ± 1.342^{a}	15.454 ± 1.331^{b}	21.410 ± 0.904^{c}	13.961 ± 0.890^{b}	19.143 ± 0.981^{c}
Co	0.009 ± 0.001^{a}	0.016 ± 0.001^{b}	0.022 ± 0.001^{c}	0.013 ± 0.001^{ab}	0.018 ± 0.003^{b}
Cu	0.536 ± 0.048^{a}	1.540 ± 0.107^{b}	2.293 ± 0.113^{c}	1.516 ± 0.094^{b}	2.417 ± 0.113^{c}
Zn	3.227 ± 0.270^{a}	6.228 ± 0.501^{b}	8.507 ± 0.506^{c}	5.838 ± 0.150^{b}	8.248 ± 0.445^{c}
Mo	<LOD	0.518 ± 0.026^{a}	0.882 ± 0.030^{b}	0.420 ± 0.016^{c}	0.720 ± 0.040^{d}

<LOD" = below the limit of detection.
Values are mean ± SD (n = 3) on a dry-weight basis. Within a row, means sharing a superscript letter do not differ significantly (one-way ANOVA; Tukey HSD, α = 0.05).

At equal substitution level, ecotype differences were generally modest (e.g., C vs E did not differ for Fe, Zn, Mn, Mg, P, K, Cu), with significant gaps only for a few elements (Ca, Co, and Mo at 20%).

Inclusion of 10–20% DBF produces a marked mineral improvement: K, P, Mg (macro) and Fe, Zn, Mn, Cu (trace) increase in a dose-dependent manner, while Na remains unchanged (recipe effect). Ecotype-specific differences are limited and emerge only for a few analytes at a given level of substitution. Together with the proximate composition results, these data confirm that dehulled legume flours enrich gluten-free bread in key micronutrients without negative impacts on the principal technological properties evaluated.

Overall discussion

Replacing 10–20% of the Caputo base mix with dehulled bean flours (Tabacchino, Verdolino) preserved the technological performance of the breads while substantially improving their nutritional and mineral profile. Across formulations, moisture at slicing was virtually identical, and specific volume, density, bake loss, and loaf geometry (H/W) showed no significant differences—evidence that, within this inclusion window, DBF does not penalize structure or processability.

On composition, DBF produced a dose-dependent rise in protein and ash, a modest fat increase only at 20%, and the expected reduction in carbohydrates by difference; calculated energy on dry basis remained stable due to compensatory shifts among macronutrients.

Color changes were more pronounced than physical ones: the crumb became lighter than the control, whereas at 20% the crust and breadcrumb darkened and reddened, with 10% showing a milder response—an effect consistent with legume-driven Maillard chemistry and inherent pigments.

From a micronutrient standpoint, DBF markedly enriched K, P, Mg (macro) and Fe, Zn, Mn, Cu (trace) in a dose-dependent manner, while Na stayed governed by the constant salt level; Mo was detectable only in DBF breads. Ecotype effects were secondary to dose: at 10 %, Tabacchino and Verdolino behaved similarly; at 20%, Tabacchino delivered the highest protein, and a few element-specific differences (e.g., Ca, Co, Mo) emerged, whereas the major enrichment trends (K, P, Mg; Fe, Zn, Mn, Cu) remained comparable between ecotypes.

Taken together, these findings show that dehulled PGI “Fagioli di Sarconi” flours can upcycle non-compliant beans into a functional ingredient that raises protein and mineral density of GFB without compromising key baking quality; operationally, 10% DBF offers a conservative balance of nutritional gain with minimal color impact, while 20% maximizes enrichment at the cost of a more noticeable darkening of crust and breadcrumb.

Integrated Discussion and Scalability

This work shows that combining a functional ingredient innovation—DBFs from local PGI “Fagioli di Sarconi” ecotypes—with a low-cost IoT fermentation monitor can deliver gluten-free breads that are nutritionally enriched yet technologically robust. The integrated evidence across chapters can be summarized as follows.

Process and ingredient readiness. The soaking–dehydration–mechanical dehulling sequence effectively removes seed coats while preserving cotyledons, yielding a clean, stable raw material for milling. In the present baking trials, DBF behaved predictably in a Caputo-based matrix at 10–20% substitution, without requiring changes to hydration or mixing beyond the base protocol. This indicates a process-ready ingredient that can be dosed as a simple partial flour replacement.

Dough behavior and process control. Real-time monitoring (ESP32; dough height/temperature/humidity) previously showed that substitutions up to ~15% did not depress gas production/retention or the rate of rise, supporting compatibility with existing gluten-free mixes. Coupling that capability with standard operating windows (proof time, temperature, humidity) provides a practical layer of in-process control. In production, the same low-cost sensing can be used to (i) track batch-to-batch variability in fermentation kinetics, (ii) detect deviations early, and (iii) document process consistency for quality audits.

Finished-product performance. In oven bakes at 10% and 20% DBF, specific volume, density, bake loss, and loaf geometry (H/W) were statistically stable versus the control, confirming that the structuring of the crumb was not compromised. Color was more sensitive: the crumb became lighter than the control, whereas the crust and breadcrumb darkened and reddened at 20% (10% showed a milder response). On composition, DBF produced a dose-dependent increase in protein and ash and a marked enrichment in minerals—notably K, P, Mg, Fe, Zn, Mn, and Cu—while Na remained governed by recipe salt. Calculated energy on a dry basis stayed essentially unchanged, reflecting compensatory shifts among macronutrients. Ecotype effects were secondary to dose: at 10% Tabacchino and Verdolino behaved similarly; at 20%, Tabacchino delivered the highest protein, and a few element-specific differences (e.g., Ca, Co, Mo) emerged.

Scalability Considerations

The results indicate strong potential to scale this approach to industrial gluten-free bakery production:

- **Ingredient processing**. The soaking–dehydration–mechanical dehulling workflow can be transferred to pilot or industrial settings with appropriate equipment sizing and process control, producing a consistent dehulled bean flour suitable for partial substitution.
- **IoT integration**. The ESP32-based monitoring can be expanded with additional sensors (e.g., CO_2, pH, O_2) and integrated with existing line controls to enable real-time feedback and predictive control of proofing and baking steps.
- **Digital transformation**. The workflow aligns with Food Industry 4.0 (digitalization, continuous monitoring, data-driven optimization) and anticipates Food Industry 5.0 priorities (human–machine collaboration, product customization, sustainability metrics).

Taken together, the study demonstrates a holistic pathway to functional gluten-free bread development—from raw-material optimization (dehulled bean flour) to real-time process monitoring (IoT) and final product assessment—providing a practical basis for scale-up and industrial adoption.

Conclusion

This application case shows that dehulled bean flour (DBF) can be integrated into gluten-free bread formulations to raise nutritional quality—notably protein and key minerals—while preserving core technological performance. Within the validated window, doughs prepared with DBF behaved predictably and baked into loaves whose specific volume, density, bake loss, and geometry (H/W) were comparable to the control; color was the most sensitive attribute, with a milder shift at 10–15% and a darker crust/breadcrumb at 20%. In the present baking dataset, energy (dry basis) remained essentially unchanged, reflecting compensatory macronutrient shifts. Where assessed in earlier phases, sensory acceptability was maintained at moderate substitution levels, supporting practical viability.

Crucially, the work did not stop at ingredient selection. An optimized pre-treatment/dehulling workflow produced a flour suitable for partial substitution without changes to the base mixing protocol. In parallel, an ESP32-based IoT system delivered continuous, reliable measurements of dough height, temperature, and humidity, enabling quantitative assessment of fermentation dynamics and offering a low-cost pathway to in-process control. Together, these elements constitute a coherent, data-driven framework that links raw-material valorization (upcycling non-compliant PGI beans) to process monitoring and finished-product quality.

From a scalability standpoint, ~10–15% of DBF offers a conservative adoption point with clear nutritional gains and minimal visual impact; 20% maximizes enrichment but calls for explicit color specifications or minor bake-profile adjustments. The IoT layer can be expanded (e.g., CO_2, pH, O_2) and integrated with existing PLC/SCADA to support predictive control, performance documentation, and continuous improvement.

Aligned with Food Industry 4.0 and anticipating Industry 5.0 priorities (human–machine collaboration, customization, sustainability), the combined ingredient-plus-digital strategy provides a practical blueprint for smart, sustainable gluten-free bakery production—improving product quality and process efficiency while strengthening territorial identity and circular-economy outcomes.

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