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Revolutionizing Food Product Development: Use of AI in Product Formulation, Sensory Prediction & Sustainable Scaling

Muhammad Azeem[1*], Mahnoor Saleh[1], Anum Tauqir[2], Muhammad Waqas[3], Fizza Arshad[4], Hafiz Muhammad Fayyaz[5], Amna Zainab[6], Fawad Khan[7]

[1]National Institute of Food Science and Technology, University of Agriculture, Faisalabad
[2]School of Health Sciences (Nutrition and Dietetics), University of Management and Technology
[3]Department of Human Nutrition, Bahauddin Zakriya University Multan
[4]Department of Food science and Technology (FFSN), Bahauddin Zakriya University Multan
[5]Department of Human Nutrition and Dietetics, Faculty of Food science and Nutrition, Bahauddin Zakariya University Multan, Pakistan
[6]Department of food science and technology, Government College University Sahiwal Campus
[7]Department of Agronomy, University Abdul Wali khan University Mardan

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***Corresponding author:** Muhammad Azeem
National Institute of Food Science and Technology, University of Agriculture, Faisalabad

Abstract **Review Article**

Conventional food research and development (R&D) is bedeviled with critical inefficiency in long-term empirical method, resource-scaled prototyping, and disintegrated consumer data, in turn preventing the provision of a novel, sustainable, and differentiated item. Current review summarizes evidence that Artificial Intelligence (AI), through machine learning, generative modeling, digital twins, and natural language processing, is changing food R&D into a data-driven paradigm. Significant breakthroughs indicate the presence of tremendous efficiencies: AI-informed formulation can cut physical prototypes to 70190 % and shorten complex reformulations to weeks, predictive analytic can predict sensory profiles with 8592 % accuracy, shaving consumer testing by 60 %, physics-informed digital twins can optimize for scalability in manufacturing, reducing scale-up runs to 4070 %, and energy usage by 1525 %, and NLP-powered trend analysis can pinpoint new opportunities 612 months before sales All together, AI reduces the development cycle by 50-60 percent and reduces R&D costs by 30-60 percent and permits sustainable innovations and hyper-personalized products. The most pervasive issues remain: the lack of data regarding new ingredients, lack of information on most algorithms, a lack of an infrastructural platform to support a small and medium-sized enterprises, and an absence of regulation regarding AI-created foods. However, even amid these thoughs, AI becomes a strategic necessity, and bringing the R&D beyond the reactive type of innovation into an anticipatory one and establishing it as one of the key enablers of competitive resilience becomes its goal. The upcoming steps will rely on cross-functional data standards, ethical data control, and democratization of access to AI in order to utilize the potential offered by the technology to its fullest extent to address the global needs in terms of healthier, sustainable, and flexible food systems.

Keywords: AI in food R&D, sustainable food tech, AI solutions, innovation in foods.

INTRODUCTION

The food industry all around the world is under continuous pressure to become innovative. This is compounded by the requirements for rapid speeds to market and cost competitiveness that are put on collision courses by emerging consumer demands of healthier and more sustainable and personalized products (Agrawal, *et al.*, 2025). The most significant part of this challenge is the classic product development cycle (Valenzuela-Melendres *et al.*, 2021). The fact that such an approach would involve a lot of time-consuming and cost-prohibitive trial and error experimentation at the ingredient sourcing, formulation, sensory analysis, and stability testing level means that, in itself, it represents a severe bottleneck (Licitra *et al.*, 2023). The process of testing iterations through numerous physical prototypes in the search of achieving the target desired nutritional profiles, taste, texture, shelf life, and cost goals and lasts months or even years, which is a considerable resource consumption and hurts innovation (Rathore, *et al.*, 2021).

Artificial Intelligence (AI) is becoming an impulse paradigm, and the sphere of food research and development (R&D) is slowly changing under its influence (Misra *et al*., 2020). With such capabilities as the results of the integration of machine learning (ML), predictive modeling, and complex data analytics, AI-enabled platforms will offer unprecedented opportunities to achieve faster formulation, better use of manufacturing processes, and reasonably predict the behavior of products in silico (Wang & Liu, 2025; Chen *et al*., 2022). These tools examine large amounts of data including ingredient properties, sensory science, consumer preferences and supply-chain parameters, hence allowing quick filtering of viable formulations (Zhang *et al*., 2023), the ability to predict sensory profile (Garcia *et al*., 2023), optimization of nutritional profile (Sharma & Lee, 2021) as well as predicting of early stability challenges before making physical prototypes (Martinez *et al*., 2020).

In the given review article, the current status of the rising implementation of artificial intelligence (AI) to hasten food research and advancement (R&D) is analyzed and synthesized. It explores the way that different branches of AI, namely predictive modeling, generative AI to design new ingredient combinations, computer vision to establish quality control, and natural language processing to mine consumer insights are already being implemented into the product development pipeline to accelerate the whole process and allow creating higher quality products that would be more likely to meet the consumer needs. In so doing, the review notes how these tools can enable food technologists to provide more innovative solutions faster and in a more efficient manner and with that, create a new era in data-driven innovation in the food industry. Major applications, existing triumphs, setbacks, and future directions in the food formulation and development transformation are hence discussed.

Accelerating Formulation & Ingredient Innovation

This step of the formulation, is the main bottleneck of classic research and development of food, in which in the past, empirical knowledge, heuristic protocols, and tandem prototyping protocols with an inefficient use of time, high resource consumption in experiments, and limited human abilities to navigate complex multivariate parameters have been used (Pradal & Datta, 2018). Artificial intelligence, especially highly developed machine learning and generative modeling, is changing this paradigm, enabling in-silico prediction, as well as intelligent design of food formulas, and their key functional, nutritional, and sensory properties (Li *et al*., 2023). The focal point of this acceleration is the ability to generate a recipe using AI and the ability to explore novelty systematically. Those incorporating Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs), or Deep Reinforcement Learning algorithms which have been trained over large data sets containing current formulation of products, passable repositories of ingredient functionality data, and past levels of success can be left to self-recommend potential ingredient constellations or entire recipes meeting multidimensional constraints.

The ability to explore volumous, historically inaccessible combinatorial space results in development teams having a more empirically informed, experiment-saving originating composition, significantly reducing the historically lengthy, and often not fruitful, pilot-plant stage. In specific terms, machine-learning (ML) practices especially come to the fore to provide precision reformulation with the help of the predictive accuracy that helps lower nutritional content and maintain functional integrity (Zhang *et al*., 2023). Lucrative computational frameworks, often under-stepped by multivariate regression, artificial neural networks (ANNs) or support vector machines (SVMs) eat formulation data and may interpolate the multidimensional results of architectural repairs. By so doing, such models are expecting downstream impacts on parametric properties that are directly relevant to product stability and microstructure (water activity, emulsion stability, viscosity, crystallization behavior), and they also predict downstream sensory perception and, hence, consumer hedonic response (Ares *et al*., 2021).

Proper elucidation of the lowest acceptable concentrations of substituting ingredients, combined with full simulation of the multifactor, often non-linear effects of partial scalecut in all constituents present simultaneously, allow artificial-intelligence-supported optimization tracks that greatly decrease the empirical trial-and-error that had traditionally been necessary to arrive at palatable, workable low-fat, low-sugar, or low-salt formulations. The requirements that ingredient replacement under the influence of clean labels, increased sustainability, cost savings, or free-from allergens brings to bear are also translated. Predictions of functional equivalence within current artificial-intelligence models requires the correlation of the physicochemical descriptors, as well as molecular structures of alternative ingredient candidates with their performance in target application matrices. Most importantly, these systems are not tied to the simple suggestion of one-to-one replacements, predicted consequent changes to other elements of the formulation or process conditions are predicted to be needed to replicate desired functionality and sensory attributes, the ability to do this with reasonable accuracy allows complex reformulation across the shortest of time horizons to be realistic. The latest fascinating and most urgent issue of the sensory analysis is the possibility of a priori prediction of sensorial and textural profiles.

By using advanced machine-learning, powerful quantitative structure-property relationships (QSPRs) can now be built between quantitative formulation features and conditions, any given instrumental measurements, and, most importantly, attributes based on human sensory panel data that have been historically described that date back to the 1950s (Miyazawa *et al*.

2022; Chen *et al*. 2021). Because of these capabilities, real virtual prototyping is now possible: food technologists can digitally assess the myriads of digital formulations and obtain timely predictions of essential sensory and textural targets. The technique in question provides a process that is typified by rapid and resources-efficient iterations, sensitivity analysis with the aim of defining decisive leverage and the ability to eliminate candidate formulations at the early stage when improper sensory properties or any establishment-related inadequacies are expected, thus avoiding the utilization of any tangible resources (Zhang *et al*. 2023).

The word efficacy in the modern prediction system is ruthlessly reliant on the magnitude, dimension, and affair of the data flow that it consults into the past formation databases, gigantic libraries of property data, analytical outcomes, cream panel tests, consumer trial information, and, not long ago, unstructured data filtering by natural language processing (NLP) (Zheng *et al*., 2023). Taken together, these abilities that involve AI create a paradigm shift to a computationally guided design paradigm as formulation is moved beyond an overly empirical, bench-oriented discipline. This kind of transformation dramatically can lower the number of physical prototypes required (by many orders of magnitude), shrinks timelines in development from months or years to weeks, lowers material and labor costs, and allows R&D teams to cover an appreciably broader, more revolutionary, design space of next-generation food products (Pradal & Datta, 2020).

Streamlining Sensory Science & Consumer Preference Prediction

The accelerated production of food products based on in silico modelling has been found to rationalize the product development process but product acceptability as guided by human sensory response and consumer palatability still form the final test of verification of these formulations. Traditional evaluation such as massive descriptive panels and consumer testing becomes a critical bottleneck in terms of its time consuming and demanding characteristics. In recent times, Artificial Intelligence has begun to overcome this shortcoming by quickly generating practical conclusions based on various sensory and consumer information. Machine-learning (ML) algorithms (including support vector machines (SVMs), random forests, and artificial neural networks (ANNs)) are trained under supervision and define the relation between instrumental measures or formulation variables and the evaluation of particular product properties by the panelists trained before (Torres *et al*., 2021).

The machine-learning methods permit real time or nearly real-time, high-resolution prediction of sensory profiles of new formulations based on instrumental data and they eliminate the backdated long cycle scheduling and execution times inherent in the testing of consumer panels. In regard to the consumer insights, artificial intelligence can serve as especially effective at processing unstructured corpora of feedback that can be of a large size. And even in their approaches that rely on natural-language-processing tools into which rich qualitative data are fed through open-ended survey questions, social media dialogue, product reviews, and focus-group transcripts, they find abundant qualitative data in previously unimaginable quantities both spatially and at different times (Wang *et al*., 2023). This type of analysis will indicate emergent themes, latent preference structures, emotive determinants and fine-grained lexical descriptions of liking or disliking which structured scales generally fail to address. Heterogeneous data modalities single-modal measures, multimodal composites, descriptive panel scores, hedonic ratings, and demographic covariates are currently combined in machine-learning models. The resulting outputs are not only liking predictions of holistic consumer liking but results on modality-specific preference profiles of discrete segments (Ares *et al*., 2022). The analytical protocols such as partial least squares (PLS) regression and other deep-learning models allow observing non-linear effects and isolating the key drivers of consumer liking (Tenenhaus *et al*., 2019; Yang *et al*. 2021).

Artificial intelligence-powered predictive models can allow the quantitative interpolative assessments of the acceptability values of virtual prototypes in the absence of physical manufacture of samples altogether, allowing timelier optimization of formulations towards both objective and determinate sensory characteristics proven to be most attractive to specific demographically constituted cohorts. This acceleration is intense: AI resolves the need to rely on sequential, extended human panels, obtains a number of consumers verbatims in a relatively short amount of time that would typically have to be examined manually over months, and allows identifying nuance in preference trends that would otherwise be unavailable when using conventional analyses. In turn, such systems provide statistically sharper, predictive instructions to the formulation adjustments within a day range instead of weeks or months previously applied towards sensory and consumer research (Siche, 2020). Sensory validation in effect, shifts off of a retrospective measure to an active, iterative cycle of feedback that is inherent in the development process.

Optimizing Processing & Manufacturing Scalability

The transfer of laboratory-scale formulations to a scale able to maintain flow of consistent, economical, and high-quality production is a common challenge of food research and development. The scale-up stage and process traditionally require large-scale pilot-plant testing to empirically optimize the processing conditions and mitigate the associated risks and, thus, consume significant amounts of raw materials, time, and funds (Rogers *et al*., 2022). The role of experimental prototyping in offering the accuracy required to overcome this dependency is being weakened by

Artificial Intelligence, particularly, state-of-the-art machine-learning approaches that are made possible by a physical model of the process. The digital twin is an active data-driven simulations model that is an accurate representation of a processing line or unit operation that is dynamically responsive. The goal in achieving this is through an ongoing synthesis of internal chemical explanations and process-operational data acquired in real time and which had been accumulated due to previous performance monitoring efforts (Trabelsi *et al*., 2023).

Multi-physics simulation frameworks that are enhanced using machine learning surrogate models are currently used to predict important process behavior over an operating spectrum (Misra *et al*., 2020). Examples of its accurate predictions during thermal processing are thermal profiles and lethality, during extrusion and shearing processes texture development and microstructure evolution, during baking moisture migration and crust formation, in fermentation microbial kinetics and production of metabolites, during a spray drying process particle size distribution and stickiness, and during an emulsification process, phase separation stability (Fundira *et al*., 2024). This allows a significant optimization of processes in entry: the shifts can devise thousands of virtual settings by adjusting screw speeds, temperatures, residence times, shear rates, feed compositions, or cooling profiles and reveal parameter combinations that yield are produced: those minimizing energy use, stay safe, attain desired qualities, and avoid faults far before prototype hundred and real experiments can be started (Zhu *et al*., 2023). The amount of necessary benchtop and pilot-scale experiments is drastically lowered as a direct result of this virtual experimentation.

In more conservative scale-up approaches, issues like unbalanced heating, variation of texture, and balky yield of a product commonly require several sequential physical batches to address. On the other hand, simulations directed with the help of AI shrink the plausible parameter area, often cutting how many physical validations runs required by 40 to 70 % and cutting long-term scale-up schedules that ordinarily take months to weeks (Li & Zhang, 2023). Digital twins become real-time decision support systems once they are implemented. Foreshadowing predicts the condition ahead and compares continuously with real-time sensor measures, with anomalies detected by machine learning, and prescriptive analytics providing suggestions of how to adjust to optimize the condition. In this process the first-pass yield can be increased, wastes eliminated, and consistent quality achieved without having to perform off-line checks at prohibitive levels (Schmid *et al*., 2022). Taken together, AI-simulations re-classify scale-up as a predictable, computer-driven process, in which advances accelerated by in silico formulation and sensory prediction can easily slip into the commercial realm, without costly hold ups or quality constraints.

Accelerating Ideation & Opportunity Identification

The first step of the food innovation process, as including clarification of the emerging consumer need, new ingredient opportunities, and trends occurring in the market, has traditionally relied on highly fragmented manual research, delayed analysis of sales data, and gut instinct, thus encouraging the reactive development cycle over the proactive one and negatively affecting the potential to miss big opportunities (Klerkx *et al*., 2019). This front-end of R&D is being revolutionised by the application of Artificial Intelligence, specifically advanced natural language processing (NLP), network analysis, and predictive analytics, which can be used to mine large volumes of diverse data streams rapidly, and in a systematic and controlled way, to identify potentially useful insights in a large volume of heterogeneous data (Caputo *et al*., 2021; Gupta & Pandey, 2023). AI models consume and digest billions of unstructured text data all over the globe the screeds of global social media, the food blogs and recipe-sharing sites, the food review literature, the scientific articles, the patent applications, the regulatory documents, the meta-data and the news feeds (Rejeb *et al*., 2022; Misra *et al*., 2023).

Today, driven by the requirement to track finer levels of change of consumer sentiment, transformer-based models and recent topic-modelling techniques have become staples of NLP research. These methods will allow advanced semantic study, which can identify gradual shifts in consumer preferences regarding products, new preferences on flavors, new dieting ideologies, and lack of satisfaction with the current product range (Cui *et al*., 2025). In turn, and complementarily, emergent ingredient concepts are now being tracked through the deployment of artificial intelligence to extract new compound mentions in scientific abstracts, patent landscape monitoring of extraction or stabilization breakthroughs and adoption profiles of niche ingredients across jurisdiction and product sector.

The network analysis algorithms enable researchers to define the associations among the nutrients, health claims and consumer demographics within large data sets hence revealing latent groups (Khan *et al*., 2021) or map the possible future directions by monitoring the diffusion patterns in neighboring markets (Olan *et al*., 2022). At the same time, predictive trend modeling is a combination of time-series forecasting and machine-learning, which predicts the potential of observed trends and makes it possible to leave out transient fads and focus on long-running movements (Wu *et al*., 2025).

The accelerating role of AI has an amplifying impact on ideation: the impact of continuously prospecting the landscape of world information near real-time is that months of manual desk research consume just hours (Lezoche *et al*., 2023); prospecting weak signals, new trends can occur several months or even years earlier than they are measurable in aggregate sales data (Annosi *et al*., 2023; Lezoche *et al*., 2023); the opportunity size and target demographics can be measured at a granular level (Balakrishnan *et al*., 2021). According to Frederik (Annosi *et al*., 2023), ideation is transformed into a never-ending, data-intensive engine of pre-emptive innovation (but not intuitive one-off event) and, by doing so, Frederik make sure that iterative development process remains in sync with the anticipated market changes that it has already outlined (Roscoe *et al*., 2022). Recent empirical research demonstrates that there is quantitative evidence of AI impact on research and development on food. The specific results noted in Table 1 highlight the shortening of development schedules and cost, as well as the needs of innovation to a more extensive degree.

Table 1: Use of AI in different areas in R&D

Application Area	AI Techniques Used	Key Findings	References
Accelerated Formulation	Generative AI (GANs, VAEs), ML, QSPR modeling	Reduced physical prototypes by 70–90%; achieved low-sugar reformulation in 3 weeks vs. 6 months traditionally.	Zhang *et al*. (2023); Doherty *et al*. (2021); Granato *et al*. (2021)
Sensory & Consumer Prediction	ANN, SVM, NLP, Deep Learning	Predicted sensory profiles with 85–92% accuracy; cut consumer testing time by 60%.	Ares *et al*. (2022); Torres *et al*. (2021); Pandey *et al*. (2023)
Manufacturing Optimization	Digital Twins, Physics-Informed ML	Reduced scale-up trials by 40–70%; energy savings of 15–25% in thermal processing.	Fundira *et al*. (2024); Li & Zhang (2023); Schmid *et al*. (2022)
Market Ideation	NLP, Transformer Models, Network Analysis	Identified emerging trends 6–12 months before sales data; mapped niche ingredient adoption.	Wang *et al*. (2023); Annosi *et al*. (2023); Gupta & Pandey (2023)
Sustainability Impact	Multi-Objective Optimization, Predictive Analytics	Reduced animal-derived ingredients by 30–50%; lowered waste in production by 20%.	Gupta *et al*. (2023); Kirtil *et al*. (2023); Chamara *et al*. (2020)

Benefits and Strategic Imperative

A well-orchestrated application of artificial intelligence throughout the food R&D value chain (including AI-enhanced ideation, in silico formulation, rapid sensory forecasting, digital process twins, and trend forecasting) provides a series of benefits that is more than just productivity and spans to the fundamental needs and operations of the modern food industry (Misra *et al*., 2023; Caputo *et al*., 2021). Remarkably, AI has the potential to shorten development cycles of products by 5060 %, and reduce R&D spending by 3060 %, by various means, including the overall use of high-cost physical prototypes, faster sensory and stability testing regimes, and faster scale-up by predictive optimization (Chen *et al*., 2024; Kirtil *et al*., 2023). More importantly, AI enables us to explore avenues out of the scope of traditional creativity. AI can enable a developer to eliminate cognitive limitations and design tasks previously considered impossible by computationally screening many ingredient combinations (Doherty *et al*., 2021), predicting clean-label or sustainable functional replacements (Gupta *et al*., 2023) and modelling multivariate product characteristics. The outcome is that new product categories are created, improved nutritional compositions and sensory experiences are developed and that are thoroughly tested before being produced (Oyinloye & Yoon, 2024; Kumar *et al*., 2022).

The enhancing of responsiveness in the market is one of the key competitive benefits. By turning to artificial intelligence and capturing the real-time social sentiment firms can do three things at once, monitor adoption of newer ingredients in recent times, trace how regional taste preferences are shifting, and extract contextual information to understand what consumers are feeling or thinking. This kind of intelligence allows product developers to create, pilot and launch products much faster than before, perhaps shortening the conventional decades-long ideation-to-launch process to a matter of months (Roscoe *et al*., 2022; Gupta *et al*., 2024). Such a proactive frame allows innovation to meet future demand, that has been validated, rather than current mentors in the marketplace (Annosi *et al*., 2023). While at the same time the values of sustainability are huge and complex. Artificial intelligence-based formulation minimises the reliance on resources-intensive animal-derived components (Gupta *et al*., 2023), optimisation of processes predicts helps to restrain the use of energy and reduce waste (Kirtil *et al*., 2023; Chen *et al*., 2024) and stability tests can be faster (Oyinloye & Yoon, 2024). In addition, trend spotting promotes prioritisation in the circular economy opportunities (Chamara *et al*., 2020). The associated risk-mitigation capabilities are also implicit: the potential formulation and process failures are detected early using virtual prototyping (Kumar *et al*., 2022); predictive stability models are utilised to assure stability on the shelves (Oyinloye & Yoon, 2024); and integral acceptability modelling can be used to assure successful product launch through alignment with empirically validated sensory motives (Balakrishnan *et al*., 2021; Pandey *et al*., 2023).

The trend of increased pace of modern food innovation ecosystem can be accurately described as the paradigmatic shift that has decisively moved the entire paradigm of sequential siloed development practices to integrated data-driven systems of innovation (Klerkx *et al*., 2019; Roscoe *et al*., 2022). In that framework, artificial intelligence (AI) reverses R&D to an innovation driver engine, allowing it to be less cost-focused and more focused on adaptive cycles of experimentation and rapid adjustment to changing market realities (Annosi *et al*., 2023; Chen *et al*., 2024). At the same time, rising consumer demand regarding health, sustainability, and individuality, along with supply-chain unpredictability and margin-pressure limitations, call to indicate that the AI is not just a mechanism of efficiency but of competitive necessity to businesses determined to dominate the food environment of tomorrow (Misra *et al*., 2023; Venkatesh *et al*., 2024). By extension, the ability to convert the ideas of the consumer into high-quality, sustainable, and commercially viable products has also become one of the most critical strategic needs, and the AI-driven acceleration provides the core of its facilitating power (Gupta *et al*., 2024; Annosi *et al*., 2023).

Challenges and Limitations

Such is the power to transform things, yet the implementation of artificial intelligence (AI) in the food and agricultural research and development (R&D) area has limited access due to various heavy challenges. First of them is data scarcity and fragmentation, particularly when it comes to emergent ingredients, e.g. plant-based proteins and regional crops. This is how predictive performance in the context of innovation management applications often falls short of acceptable levels due to the scarce quantity of available physicochemical and sensory data (Oliveira *et al*., 2023; Zhang *et al*., 2024). Furthermore, even the algorithms themselves are not entirely transparent: deep neural-network-based models, in particular, work as proprietary black-box systems, hence disrupting the trust of technologists and regulatory compliance (Kumar *et al*., 2022). Scalability is also hindered by operational limitations, in particular, small- and medium-sized enterprises (SMEs) that do not have access to suitable computational infrastructure (e.g., cloud services at around US $20,000 per month) or knowledge in the field of machine-learning solutions (Rogers *et al*., 2023; Caputo *et al*., 2024).

Delays have been a characteristic feature of the emergence of digital health therapeutics (DHTs) that are compounded by existing ethical and regulatory challenges. As an example, patterns of algorithmic bias in consumer-preference data mining often over-represent Western preferences specifically (Gupta & Pandey, 2023), and agencies including the U.S. Food and Drug Administration (FDA) have no concrete policies by which to approve novel foods generated by AI (Oyinloye & Yoon, 2024). Taken together, these constraints reveal a dire need to bridge standards, access, and control in whatever regard that the field (or other relevant disciplines) is pursuing advancements in AI and various achievements in food research & development.

CONCLUSION

Introduction of Artificial Intelligence (AI) in food research and development represents a paradigmatic shift to put into practice the inefficiencies inherent to traditional empirical procedures. Because of the introduction of advanced methodologies such as generative modeling, predictive analytics, digital twins and natural language processing, AI creates acceleration in the R&D value chain to previously non-realizable levels. Benefits of the result are considerable: future potential decreases in the overall physical prototypes by as much as 70 90%, the development of complicated reformulations (e.g., low-sugar, under-fat consumer products) in weeks and not in months, the determination of the sensory profile with 8592percent precision and, hence, a shrinkage of consumer-testing timelines by as much as 60 percent, the optimization of manufacturing scales through the use of digital clones, the decrease of the scale-up runs by 40 70 percent. Empirical research shows that next-generation artificial-intelligence (AI) platforms have the ability to reduce the product-development timeline by 50 60 % and research-and-development costs by 30 60 %, and expand new avenues to sustainable, design-driven innovation. However, a number of obstacles still exists, among them inadequate datasets on new ingredients, transparency of the so-called black-box algorithmic models, a lack of necessary infrastructural support of small and medium-sized organizations, and an underdeveloped regulatory framework to deal with AI-generated products in terms of food. Despite these limitations, AI exceeds operational efficiency merits as a part of many routine operations to acquire strategic necessity. Supporting data-driven creativity and making speedy and nimble reaction to consumer demands and sustainability projects, akin to decimating animal-derived components by 30-50 % and decreasing production waste, AI essentially makes the R&D process anticipatory rather than reactive. The further development in this area will depend on the collaborative effort to develop normative data-ecosystem standards that will democratize the access to AI, and elaborate on complete ethical-regulatory guardrails. When faced with growing pressure on nutrition and sustainability as well as greater customization of food systems, AI-driven speeds are seen as vital to the radical industrial progress.

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