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AI-DRIVEN 3D FOOD PRINTING: TRANSFORMING FOOD TECHNOLOGY AND SUSTAINABILITY

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ABSTRACT

This systematic review explores the integration of artificial intelligence (AI) and machine learning (ML) in advancing 3D food printing (3DFP), with emphasis on customization, optimization, and emerging innovations. Recent studies (2023–2024) were reviewed to evaluate AI-enhanced 3DFP, focusing on optimization techniques, AI-driven monitoring systems, and 4D printing developments. AI-driven 3D food printing enhances food design precision, material versatility, and customization while promoting sustainability through reduced waste and novel bio-ingredients. Advances in multimaterial printing, shape-shifting capabilities, and nanotechnology integration further improve texture, nutrition, and consumer appeal, setting the stage for transformative impacts across gastronomy, healthcare, and food technology sectors. ML methods such as reinforcement learning and deep learning significantly enhance parameter optimization, material behavior, and print quality. AI facilitates real-time adjustments to extrusion force, viscosity, and structural integrity. Applications span personalized nutrition, tissue engineering, and gastronomy. 4D printing introduces dynamic, shape-shifting capabilities. Technological limitations, data quality issues, and regulatory barriers remain. Key concerns include ink printability, structural stability, and consistency. AI and 3DFP present a transformative synergy in food technology, promoting sustainability, personalization, and precision. Future research should address scalability through biocompatible materials and standardized datasets.

KEYWORDS: 3D Food Printing (3DFP), Food Sustainability, Machine Learning Algorithms, Optimization Techniques, AI-driven Monitoring Systems.

1. INTRODUCTION

The intersection of machine learning (ML) and 3D Food Printing (3DFP) is driving innovation in food production, offering solutions to the growing challenges of food customization, personalization, and sustainability. Machine learning algorithms, such as reinforcement learning and deep learning, play a critical role in optimizing various stages of 3D food printing. These algorithms enable the design and fabrication of food items with intricate geometry and customized nutritional profiles. Reinforcement learning (RL) allows adaptive optimization of 3D printing processes, such as extrusion rates and temperature control, while deep learning techniques help in predicting and improving the properties of printed foods (Agarwal et al., 2024; Alghamdy et al., 2024). These technologies contribute to the advancement of 3DFP by improving efficiency, food quality, and the ability to respond to specific dietary needs.

1.1. Issues and Gaps in 3DFP and AI Integration

While the potential for 3DFP and AI is vast, several issues remain unresolved. One of the primary concerns is the printability of food materials, specifically, how different food formulations behave during printing. Ink viscosity, shear-thinning behavior, and extrusion force are critical factors that affect the quality and consistency of printed foods (Li et al., 2024; Tian et al., 2024). However, significant gaps remain in optimizing the properties of various food inks and developing standardized methods for predicting printability across diverse food types (Derossi et al., 2023). Additionally, the integration of AI-driven systems into 3DFP faces challenges related to data quality and processing. Current AI technologies require accurate input data such as detailed patient data processing and nutritional needs prediction to generate optimized food prints for specific health conditions or personal preferences (Kokane et al., 2024). Despite progress, many AI models still lack the sophistication required for seamless integration across different stages of the 3D printing workflow, including monitoring systems, closed-loop control, and adaptive manufacturing processes (Wang et al., 2024) (Kalogeropoulou et al., 2024).

2. OBJECTIVES FOR THE REVIEW

The primary objective of this review is to examine the latest advancements in integrating machine learning (ML) algorithms with 3D food printing (3DFP) technologies. Specifically, this review will explore the optimization techniques in 3DFP, such as the influence of ink viscosity and shear-thinning behavior on the quality and consistency of printed food (Alghamdy et al., 2024). Additionally, it will evaluate the role of AI-driven monitoring systems, which enhance the printing process by providing greater precision and control, ensuring the accurate formulation and design of 3D food prints (Alghamdy et al., 2024). Moreover, the review will analyze recent innovations in 3D and 4D printing technologies, especially the use of nanomaterials and their promising applications in areas like vascular tissue engineering (Agarwal et al., 2024; Chen et al., 2024).

2.1. Scope of the Review

The scope of this review encompasses a detailed examination of various aspects of 3D food printing (3DFP) and its integration with AI technologies. It begins with an overview of 3DFP, offering a historical perspective on the technology and its current applications. This section delves into key principles such as material properties, extrusion techniques, and layer-by-layer printing methods that are essential to the 3DFP process (Wang et al., 2024). The review further investigates optimization techniques in 3DFP, focusing on factors like ink viscosity and shear-thinning behavior, and their critical influence on the consistency and quality of the printed food products. By addressing printability challenges, including food texture, stability, and appearance, the review also highlights potential solutions such as new food inks and materials to improve overall printability (Alghamdy et al., 2024; Kılınç & Kılınç, 2024; Li et al., 2024; Tian et al., 2024).

2.2. Global Comparison

The global research landscape on 3D and 4D food printing shows a dynamic evolution aligning with the review's objective of exploring how AI-driven 3D food printing is transforming food technology and promoting sustainability. Studies such as Alghamdy et al. (2024) and Tian et al. (2024) emphasize optimization of printability and printing fidelity, indicating technological advancements critical for AI integration. Works like Burke (2024) and Meijers and Han (2024) capture the gastronomic and structural evolution of 3D printed foods, resonating with the review's goal of mapping food technology transformations. From a material science perspective, research by Calton et al. (2023) and Li et al. (2024) illustrates innovations in ingredients and paste formulations to enhance food structure and nutrition, further supporting sustainability goals. The rise of nanomaterials and smart biomaterials, discussed by Agarwal et al. (2024) and Sadraei and Naghib (2024), mirrors the review's futuristic vision, bridging AI, 3D, and emerging 4D technologies. Moreover, sustainability and customization trends, addressed in Varghese et al. (2024), Wang et al. (2024), and Yang et al. (2024), align with the objectives by highlighting environmental considerations, waste reduction, and personalized nutrition. Business and commercialization insights from Nopparat and Motte (2023) also demonstrate the market viability of AI-enhanced 3D food printing, reinforcing the review's broader ambition to contextualize technological innovation within economic and ecological frameworks.

2.3. Novelty of the Review

This review distinguishes itself by offering a comprehensive exploration of the convergence between machine learning and 3D food printing (3DFP). It brings together the latest research on optimizing food materials for printing, emphasizing the role of AI-powered workflows in improving printing accuracy, efficiency, and customization. One of the key innovations discussed is the advancement of 4D food printing, which focuses on creating dynamic, responsive food materials that change shape or properties post-printing. This novel aspect presents a new frontier in food technology, offering the potential for materials that adapt to their environment or user needs (Wang et al., 2024) (Burke, 2024). Furthermore, the review introduces AI-based models for optimizing food inks, addressing the challenges of printability and improving the overall consistency and quality of printed food products, making these systems more viable for both home and industrial applications.

The review further expands the application of AI in 3DFP beyond traditional food production, investigating its potential use in areas such as personalized nutrition, patient-specific food generation, and tissue engineering. By focusing on personalized nutrition, the review explores how AI can generate tailored meals based on individual dietary needs, health conditions, and even genetic profiles. This not only opens possibilities for precision food production for medical and dietary purposes but also bridges the gap between technology and healthcare (Chen et al., 2024; Kokane et al., 2024). In addition to healthcare applications, the integration of machine learning with 3DFP can potentially enhance sustainability by reducing food waste, optimizing ingredient usage, and improving the efficiency of food production processes.

Ultimately, the review aims to address the knowledge gap between machine learning and food printing technologies, encouraging future research that blends these fields to create more sustainable and customized food production systems. The integration of machine learning algorithms with 3D food printing promises to revolutionize food production by enabling personalized, health-focused, and environmentally friendly solutions. While significant challenges remain, particularly regarding ink printability, AI integration, and process optimization, this review provides an in-depth understanding of these obstacles and suggests promising directions for future exploration. By contributing to the understanding of how AI and 3DFP can work together, the review sets the stage for breakthroughs that could reshape the future of food production, making it more adaptable to both consumer preferences and environmental demands.

3. METHODS

3.1. Eligibility Criteria

The systematic review focused on literature published between 2023 and 2024, prioritizing advancements in machine learning (ML), artificial intelligence (AI), and 3D food printing (3DFP). The eligibility criteria were designed to capture innovative, application-specific, and quantitative contributions to the field. The following key areas defined the inclusion parameters: Technological Innovations: The review emphasized the integration of advanced computational methods with 3D food printing (3DFP) to enhance performance and capabilities. Studies explored machine learning (ML) algorithms that optimized predictive modeling, enabling precise adjustments to print parameters and material behavior. Reinforcement learning was highlighted for its role in refining iterative processes in real time, thereby improving system responsiveness. Furthermore, deep learning applications demonstrated the potential of neural networks to interpret complex datasets, contributing to high precision in 3DFP operations. Collectively, these technologies addressed critical challenges such as manufacturing accuracy, scalability, and operational efficiency, paving the way for significant advancements in the field.

Application-Based Studies: A substantial portion of the review focused on practical implementations of 3DFP technology. Research detailed optimization techniques to fine-tune critical parameters, including feed rates, layer thickness, and temperature controls, ensuring improved printing outcomes. The studies often included schematic diagrams that provided visual representations of machine setups and operational workflows. Practical applications showcased 3DFP's versatility, with notable innovations in personalized food production, the development of edible materials, and advancements in tissue engineering. These applications underscored the transformative potential of 3DFP across diverse industries. Advanced Innovations: The review also delved into pioneering advancements, particularly the emerging field of 4D printing, a dynamic evolution of 3DFP technology. This innovation involves the use of stimuli-responsive materials, which can alter their structure or function post-printing in response to environmental triggers. A significant application highlighted was in vascular tissue engineering, where 4D printing enabled the creation of complex biological scaffolds for medical use. These breakthroughs demonstrated the potential for 3DFP to intersect with cutting-edge biomedical technologies. AI Integration in 3DFP: The transformative role of artificial intelligence (AI) in enhancing 3DFP systems emerged as a pivotal area of interest. Studies investigated AI-driven monitoring systems that utilized computer vision and real-time analytics to detect and correct errors during the printing process. Research into patient data processing explored personalized printing solutions tailored to individual dietary or medical needs. Additionally, AI's integration into additive manufacturing showcased its ability to design and fabricate intricate geometries with unparalleled precision. These advancements underscored AI's critical role in elevating 3DFP's potential.

3.2. Exclusion Criteria

To maintain the review's focus, strict exclusion criteria were applied. Studies that did not specifically address 3DFP technologies or focused on generalized AI applications unrelated to food or bioprinting were excluded. Additionally, research published outside the 2023–2024 timeframe was omitted to ensure the review encompassed the most current advancements. This meticulous approach facilitated a thorough understanding of the intersection of AI and 3DFP, capturing the latest developments while preserving thematic relevance.

3.3. Study Selection

The review process screened 24 references, comprising peer-reviewed journal articles, systematic reviews, and original research studies. The evaluation focused on the relevance of the abstracts, the methodological rigor demonstrated in the studies, and their contributions to advancing the understanding of AI-enhanced 3D food printing (3DFP) technologies. Each reference was critically assessed to ensure its alignment with the objectives of the review. A rigorous double-screening process was implemented to maintain consistency and objectivity in the selection. In the first stage, titles and abstracts were reviewed to exclude studies that were irrelevant or failed to meet preliminary inclusion criteria. This initial screening eliminated works that did not address the intersection of AI and 3DFP or lacked significant technological or application-based contributions. Subsequently, a full-text review was conducted for the remaining articles, focusing on their detailed methodologies, results, and implications. This in-depth analysis ensured that only studies with substantial relevance and quality were included. Finally, the selected references underwent a peer-review process to validate their objectivity and thematic alignment with the review's goals. This meticulous approach ensured that the references collectively provided a robust and comprehensive foundation for analyzing advancements in AI-driven 3DFP technologies.

3.4. PRISMA Checklist for Systematic Review

Table 1: A Detailed Mapping of Research Process and References.

Item	Description	References Used
Title	A clear, descriptive title for the review.	All References
Abstract	Structured abstract outlining the background, objectives, methods, results, and conclusion.	Agarwal et al. (2024); Burke (2024); Wang et al. (2024)
Rationale	Justification for conducting the systematic review.	Kılınç and Kılınç (2024); Wang et al. (2024)
Objectives	Define specific objectives of the review.	Wang et al. (2024); Derossi et al. (2023)
Eligibility Criteria	Criteria for including studies in the review.	Alghamdy et al. (2024); Koirala et al. (2023)
Information Sources	List of databases and sources searched.	Li et al. (2024); Kalogeropoulou et al. (2024)
Search Strategy	Detailed search strategy used for selecting studies.	Meijers and Han (2024); Varghese et al. (2024)
Study Selection	Process for selecting studies for the review.	Nopparat and Motte (2023); Chen et al. (2024)
Data Extraction	Methods for extracting data from studies.	Kalogeropoulou et al. (2024); Sadraei and Naghib (2024)
Data Synthesis	How data will be synthesized.	Tian et al. (2024); Gu et al. (2023)
Risk of Bias in Individual Studies	Assessment of risk of bias in each included study.	Kokane et al. (2024); Wang et al. (2024)
Summary Measures	Measures for summarizing data.	Li et al. (2024); Kılınç and Kılınç (2024)
Synthesis of Results	Detailed synthesis and integration of the results.	Burke (2024); Nopparat and Motte (2023)
Risk of Bias Across Studies	Address risk of bias across all studies.	Kalogeropoulou et al. (2024); Tian et al. (2024)
Additional Analyses	Other analyses performed, such as subgroup or sensitivity analysis.	Varghese et al. (2024); de Farias et al. (2024)
Results	Summary of the findings with detailed data.	Derossi et al. (2023); Kokane et al. (2024)
Discussion	Interpretation of the results, limitations, and implications.	Kılınç and Kılınç (2024); Agarwal et al. (2024)
Conclusions	Conclusion of the systematic review.	Wang et al. (2024); Alghamdy et al. (2024)
Funding	Details of any funding received.	Wang et al. (2024); Meijers and Han (2024)
Conflict of Interest	Any conflicts of interest.	All References
Authors' Contributions	Contributions of each author to the review.	All References
Acknowledgements	Any acknowledgments for contributions not included in authorship.	Wang et al. (2024); Varghese et al. (2024)

Table 1 outlines the PRISMA checklist, which serves as a structured guide for conducting a systematic review, ensuring transparency and reproducibility. Each item on the checklist corresponds to a specific component of the review process, such as defining objectives, establishing eligibility criteria, and assessing bias. The table also includes references to studies that inform or align with each step in the review process. By referencing these studies, the table helps to validate the methods and approaches used in the systematic review. This ensures that each aspect of the review, from the search strategy to the conclusions, adheres to established standards and is backed by recent research in the field.

3.5. PRIMA Flowchart

The systematic review process began with the identification of 113 records: 108 from database searches and 5 from other sources. After removing duplicates, 46 records remained, which were screened for relevance. A total of 20 records were excluded based on screening criteria. Subsequently, 26 full-text articles were assessed for eligibility, and 2 were excluded from reasons provided. Ultimately, 24 studies were included in both the qualitative and quantitative synthesis for the review. This flowchart captures the rigorous process of identifying, screening, and selecting studies for inclusion in the review.

Identification

Records identified through database searching (n = 108)

Additional records identified through other sources (n = 5)

Screening

Records after duplicates removed (n = 46)

Records screened (n = 46)

Records excluded (n = 20)

Eligibility

Full-text articles assessed for eligibility (n = 26)

Full-text articles excluded, with reasons (n = 2)

Included

Studies included in qualitative and quantitative synthesis (n = 24)

Figure 1: PRISMA Flowchart for Study Selection Process in Systematic Review.

3.6. Data Extraction

Key data were extracted systematically, and the findings were categorized under distinct thematic areas to facilitate a comprehensive analysis.

Technological Foundations: This theme encompassed foundational studies on machine learning (ML) algorithms, reinforcement learning, and deep learning, highlighting how these computational methods enhance 3D food printing (3DFP). Relevant studies such as those by Chen et al. (2024) and Wang et al. (2024) explored these technologies and their integration with 3DFP, showing how they optimize print parameter adjustments and material behavior.

3DFP Fundamentals: Research under this category provided insights into the basic principles of 3DFP, including schematic diagrams, machine setups, and its diverse applications. Articles by Alghamdy et al. (2024) and Burke (2024) discussed the versatility of 3DFP, ranging from food production to more complex applications like tissue engineering, offering detailed methodologies and visual representations of the printing processes.

Quantitative Parameters: The review emphasized quantitative studies that explored the material properties crucial for 3DFP. Works such as those by Tian et al. (2024) and Li et al. (2024) focused on rheological properties like ink viscosity, shear-thinning behavior, and extrusion forces, all critical for ensuring material flow consistency during the printing process.

Optimization & Challenges: This theme identified studies addressing printability issues and process optimization in 3DFP. Research by Derossi et al. (2023) and Gu et al. (2023) provided solutions to common printing challenges, such as optimizing feed rates, layer thickness, and temperature control, contributing to more reliable and efficient 3DFP systems.

AI Contributions: The role of artificial intelligence (AI) in enhancing 3DFP workflows was explored, with key studies like those by Sadraei and Naghib (2024) and Yang et al. (2024) examining AI-driven monitoring systems and closed-loop 3D printing systems. These innovations ensure real-time adjustments and more precise additive manufacturing.

Future Innovations: The future of 3DFP was also considered, with a focus on emerging areas such as vascular tissue engineering and 4D printing. Studies by Kalogeropoulou et al. (2024) and Sajjad et al. (2024) presented groundbreaking advancements in these areas, such as the development of stimuli-responsive materials and the fabrication of complex biological structures for medical applications.

Table 2: Key Findings on AI-Driven Advances in 3D Food Printing (3DFP).

Topic	Key Findings	References
Introduction to Machine Learning Algorithms	Overview of various machine learning algorithms used in 3D food printing (3DFP), including AI integration and reinforcement learning	Agarwal et al. (2024), Wang et al. (2024)
Reinforcement Learning	Application of reinforcement learning to optimize 3DFP processes, specifically in design features and material properties	Alghamdy et al. (2024), Kılınç and Kılınç (2024)
Deep Learning	Deep learning used for predicting nutritional needs, optimizing meal generation, and improving print fidelity	Tian et al. (2024), Varghese et al. (2024)
3D Food Printing (3DFP) Applications	Applications of 3DFP in food customization, including texture and structural optimization for plant-based meats	Calton et al. (2023), Burke (2024)
Overview of 3DFP Technology	An overview of 3DFP processes, technologies, and evolving materials in food printing, such as edible gels and bioinks	Derossi et al. (2023), Koirala et al. (2023)
3DFP Schematic Diagram	Illustration of 3DFP process flow, integrating material preparation, extrusion, and post- processing	Meijers and Han (2024), Nopparat and Motte (2023)
Optimization Techniques in 3DFP	Use of optimization methods like design feature analysis to improve printability and food properties	Alghamdy et al. (2024), Gu et al. (2023)
Quantitative Data in 3DFP	Analysis of ink viscosity, shear-thinning behavior, and extrusion force as key factors in printability	Li et al. (2024), Wang et al. (2024)
Ink Viscosity	Impact of viscosity in food inks on the precision and texture of printed food	Gu et al. (2023), Li et al. (2024)
Shear-Thinning Behavior	Shear-thinning behavior affecting extrusion consistency and quality during 3DFP	Wang et al. (2024), Tian et al. (2024)
Extrusion Force	Variations in extrusion force and their effect on material behavior and print integrity	Alghamdy et al. (2024), Derossi et al. (2023)
Printability Challenges	Challenges in printability, such as material stability, process precision, and post-printing quality	Kılınç and Kılınç (2024), Wang et al. (2024)
Printability Solutions	Solutions include optimization of material properties and AI-driven feedback loops for consistent results	Nopparat and Motte (2023), Wang et al. (2024)
Integration of AI in 3DFP	Use of AI to monitor and optimize the printing process, ensuring precision in food structure	Agarwal et al. (2024), Tian et al. (2024)
AI-Driven Monitoring Systems	AI systems help in real-time monitoring of the printing process, improving accuracy and reducing errors	Wang et al. (2024), Alghamdy et al. (2024)
AI-Augmented Additive Manufacturing	AI augmentation of additive manufacturing techniques to improve customization in food textures and flavors	Kalogeropoulou et al. (2024), Meijers and Han (2024)
Closed-Loop 3D Printing	Integration of closed-loop systems for self- correction in printing to enhance quality	Kalogeropoulou et al. (2024), Tian et al. (2024)
Advanced Innovations in 3D and 4D Printing	Development of 4D printing technology for creating shape-shifting food products and applications in tissue engineering	Kalogeropoulou et al. (2024), Agarwal et al. (2024)
4D Printing	Use of 4D printing to create food that changes shape in response to environmental stimuli, adding functionality to food design	Sadraei and Naghib (2024), Yarali et al. (2024)
Vascular Tissue Engineering	Application of 3D and 4D printing in biomedicine for tissue engineering, potentially advancing personalized nutrition	Chen et al. (2024), Kalogeropoulou et al. (2024)
AI-Powered Workflows in 3DFP	AI systems helping streamline workflows in the food printing industry, from material selection to print execution	Tian et al. (2024), Meijers and Han (2024)
Patient Data Processing	Integration of patient data to optimize meal planning, enhancing nutritional benefits	Wang et al. (2024), Kilinç & Kilinç (2024)
Nutritional Needs Prediction	AI algorithms used to predict personalized nutritional needs based on health data	Agarwal et al. (2024), Sadraei and Naghib (2024)
Optimized 3D-Printed Meal Generation	AI-driven optimization of 3D food printing to create personalized meals based on nutritional requirements	Varghese et al. (2024), Li et al. (2024)

All data points were logged into a centralized database, enabling a comparative analysis and thematic synthesis of the findings, which contributed to a clearer understanding of the convergence of AI and 3DFP in advancing manufacturing and bioprinting technologies. Table 2 provides an overview of the integration of machine learning, AI, and innovative technologies in 3D food printing (3DFP). Key findings highlight the use of reinforcement learning and deep learning algorithms to enhance food customization, including nutritional needs prediction and meal generation optimization. The table also explores the challenges and solutions related to printability, such as viscosity and extrusion force, along with advancements like 4D printing and AI-driven monitoring systems for precision in food structure. Additionally, the application of AI-powered workflows streamlines 3DFP processes, ensuring the creation of personalized meals and optimizing nutritional benefits through patient data integration. Key developments also include the exploration of vascular tissue engineering and 4D printing technologies, which offer potential advancements in personalized nutrition and shape-shifting food products.

3.7. Data Synthesis

Using a thematic analysis approach, the extracted data were synthesized into distinct sections that comprehensively address the key advancements in machine learning (ML) and 3D food printing (3DFP).

Introduction to Machine Learning in 3DFP: Several studies emphasized the critical role of ML algorithms in 3DFP, particularly in predicting and optimizing printing parameters for greater accuracy in additive manufacturing. ML algorithms facilitate the adjustment of print parameters in real time, ensuring consistent quality. Reinforcement learning and deep learning techniques were central in creating adaptive systems that improve over time based on feedback, optimizing both the manufacturing process and material behavior (Agarwal et al., 2024).

3DFP Applications and Innovations: The review highlighted a wide range of applications facilitated by the convergence of 3DFP with advanced technologies. This included the generation of personalized meals tailored to specific dietary requirements, as well as breakthroughs in tissue engineering, which leverage both 3D and 4D printing methods. These innovations are transforming not only food production but also medical applications, with significant progress made in the customization of edible materials and the development of bioprinted tissues (Chen et al., 2024; Kokane et al., 2024).

Optimization Techniques: Quantitative studies on material properties were central to enhancing the printability and fidelity of 3DFP systems. Research on ink viscosity, extrusion mechanisms, and shear-thinning behaviors provided valuable insights into the complex rheological properties required for consistent extrusion and deposition. These studies are essential for improving material flow and print precision, addressing the critical need for reliable and scalable 3DFP systems (Li et al., 2024; Tian et al., 2024).

AI Integration: The integration of AI into 3DFP technologies was another focal point of the review. AI-powered monitoring systems, which use computer vision and machine learning algorithms, enable real-time analysis and error correction during the printing process. These systems are essential for ensuring high precision in both food and healthcare applications, particularly in personalized printing solutions. The use of closed-loop systems, where AI algorithms adjust parameters in response to real-time data, has significantly enhanced the accuracy and reliability of 3DFP processes (Sadraei & Naghib, 2024).

Challenges and Solutions: The review also examined common challenges faced in 3DFP, such as nozzle clogging, material instability, and the difficulty of achieving optimal print quality. These challenges were mitigated through the development of advanced ink formulations and machine learning-driven optimization strategies. The implementation of reinforcement learning techniques has proven effective in minimizing errors and improving the robustness of 3DFP systems (Derossi et al., 2023; Gu et al., 2023).

Future Directions: The review concluded with a discussion of future directions for 3DFP, focusing on emerging 4D printing technologies. These technologies, which incorporate stimuli-responsive materials capable of changing their properties post-printing, hold great potential for creating dynamic, multifunctional constructs. Such innovations are expected to revolutionize fields like tissue engineering by enabling the fabrication of more complex and responsive biological structures (Kalogeropoulou et al., 2024; Sajjad et al., 2024).

4. RESULTS AND FINDINGS

4.1. Reinforcement Learning in 3DFP

Reinforcement learning (RL), a subfield of machine learning, focuses on optimizing decision-making in dynamic environments through trial-and-error interactions with the system, guided by feedback mechanisms. In the context of 3D food printing (3DFP), RL-based adaptive control systems dynamically refine the printing process, improving performance, reducing errors, and enhancing material efficiency.

Dynamic Parameter Adjustments: RL models are uniquely capable of adjusting critical extrusion parameters such as speed, pressure, and temperature in real time, responding adaptively to environmental and material variations. For instance, Alghamdy et al. (2024) demonstrated how RL algorithms leverage sensor data such as real-time measurements of material viscosity, nozzle output rate, and ambient temperature to recalibrate operational settings dynamically. This capability ensures consistent material flow, improving layer uniformity and reducing structural anomalies. By continuously optimizing these parameters during printing, RL minimizes the likelihood of process interruptions or suboptimal layer deposition, contributing to higher print fidelity and product quality.

Error Reduction and Material Efficiency: One of the standout features of RL systems in 3DFP is their integration of predictive feedback loops, which recognize and mitigate printing inconsistencies before they escalate. For example, layer misalignment or over-extrusion is detected through real-time monitoring, prompting the system to autonomously adjust parameters to restore precision. This capability not only maintains structural integrity but also reduces material wastage significantly by up to 25%, as noted by Alghamdy et al. (2024). This efficiency is especially critical when printing with high-cost or specialized materials such as bioactive compounds or sustainable edible inks, where minimizing waste directly translates into cost savings and environmental benefits.

4.2. Deep Learning in 3DFP

Deep learning (DL) has become an indispensable tool in 3D food printing (3DFP), transforming its capabilities through enhanced data processing, predictive modeling, and real-time optimization. Convolutional Neural Networks (CNNs), a core DL architecture, excel in analyzing multidimensional datasets, enabling unprecedented precision and customization in 3DFP processes.

Rheological Data Analysis: Rheological properties such as shear-thinning behavior, yield stress, and viscosity curves are critical in determining the flow dynamics and layer adhesion in 3DFP. DL algorithms, particularly CNNs, analyze extensive datasets containing these properties to predict and fine-tune optimal extrusion parameters. For example, Tian et al. (2024) demonstrated how CNNs integrate input from viscometers, flow meters, and other rheological instruments to model material behavior under varying conditions. These models enable the prediction of stable extrusion force, ensuring consistent material flow and uniform deposition, even with complex edible inks or bioengineered substances.

4.3. 3D Food Printing (3DFP) Applications

Culinary Artistry and Gastronomy: 3DFP is revolutionizing the culinary arts by enabling chefs and food designers to create complex, intricate, and visually striking food structures. The technology supports the production of themed edible sculptures, multilayered desserts, and customized plating elements that were previously unattainable using traditional techniques.

Burke (2024) highlighted its impact on experiential dining, where consumers seek tailored and immersive food experiences. By integrating texture control, precision layering, and material diversity, 3DFP aligns with the growing demand for creative and personalized dining solutions, enabling the creation of visually appealing and structurally unique dishes that push the boundaries of gastronomy.

Innovative Food Prototyping: 3DFP accelerates the development of novel food products by enabling rapid prototyping and testing. Functional foods enriched with bioactive compounds, alternative proteins, and plant-based inks can be precisely formulated and printed to achieve desired taste, texture, and nutritional profiles.

Derossi et al. (2023) explored the role of 3DFP in creating sustainable food solutions, such as printing with protein-rich insect flours or algae-based bioinks. This innovation not only supports the development of environmentally friendly food alternatives but also allows for iterative design adjustments, reducing development time and waste while ensuring consumer acceptance.

4.5. 3DFP Technology

The integration of artificial intelligence (AI) into the 3DFP process has introduced a new level of precision and adaptability. AI algorithms can optimize material deposition, adjust extrusion parameters in real-time, and ensure consistent quality throughout the printing process, effectively reducing human error and improving operational efficiency. Meijers and Han (2024) proposed the "3D Food Printing Pyramid" to categorize these technological advancements, offering a structured framework that organizes innovations into tiers ranging from fundamental 3DFP techniques to advanced AI-driven applications. This pyramid helps identify gaps in current technology and suggests potential directions for future research, such as enhancing material properties, optimizing machine learning models for real-time control, and developing more scalable production methods.

4.6. 3DFP Schematic Diagram

In this context, Chen et al. (2024) provided a detailed schematic diagram outlining the entire 3DFP workflow, from initial material preparation to post-printing processes. These diagrams serve as a visual guide for understanding the sequential stages of 3DFP, which include material selection, ingredient formulation, extrusion, layer deposition, curing, and finishing. The integration of AI systems is particularly highlighted at each stage of the workflow, ensuring that transitions between steps are smooth and that output quality is consistently maintained. For example, AI systems can monitor material flow during the extrusion process, adjusting parameters like extrusion speed and pressure based on real-time data to ensure uniform deposition.

4.7. Optimization Techniques in 3DFP

In 3D food printing (3DFP), optimization techniques are fundamental to ensuring high-quality, precise prints, especially when dealing with complex structures that require intricate layer deposition and material consistency. Wang et al. (2024) emphasized the critical role of parameters such as ink viscosity and extrusion force in maintaining print fidelity. Ink viscosity is particularly important for controlling the flow dynamics of the food material.

Viscosity determines how easily the material flows through the extruder nozzle and adheres to previously deposited layers, directly influencing the print's structural integrity. High-viscosity inks may lead to clogging or uneven extrusion, while low-viscosity inks could result in poor layer adhesion or material sagging. Therefore, precise control over ink viscosity is crucial to ensure uniform material flow, consistency in deposition, and minimal errors during the printing process.

4.8. Quantitative Data in 3DFP

Ink Viscosity: Gu et al. (2023) demonstrated that controlling the viscosity of the ink is essential for achieving stable and consistent flow dynamics during extrusion. Viscosity refers to the thickness or resistance of a material to flow; in the context of 3DFP, it governs how easily the material moves through the extruder nozzle. If the viscosity is too high, the ink may flow too slowly, leading to blockages or inconsistencies in deposition.

On the other hand, low viscosity can cause the material to spread too quickly, potentially resulting in poor layer adhesion and structural integrity. By precisely controlling viscosity, it is possible to regulate the flow behavior of the material, ensuring that it deposits smoothly, adheres well to previous layers, and maintains its intended shape during the printing process. Gu et al. (2023) showed that optimized ink viscosity not only facilitates smoother extrusion but also enhances print quality by improving the consistency and precision of layer deposition.

Shear-Thinning Behavior: Alghamdy et al. (2024) highlighted the importance of shear-thinning behavior in 3DFP materials. Shear-thinning refers to a material's ability to decrease viscosity when subjected to stress or shear forces, making it flow more easily under pressure. In 3DFP, materials that exhibit shear-thinning behavior are particularly useful because they adapt well to the changing pressure conditions during extrusion.

For instance, when the material is extruded through the nozzle, it experiences shear forces that cause it to flow more easily, allowing for smoother deposition of the material onto the build surface. After extrusion, the material's viscosity increases again, solidifying and maintaining its shape. This property is critical for maintaining print stability, as it ensures that the material flows evenly during the printing process and prevents common extrusion issues such as clogging or over-extrusion. Alghamdy et al. (2024) demonstrated that materials with shear-thinning behavior can better accommodate variable pressure conditions, improving the overall reliability and precision of the 3DFP process, especially for complex and fine geometries.

Extrusion Force: Tian et al. (2024) emphasized the significance of consistent extrusion force in 3DFP, particularly for ensuring high-resolution prints. Extrusion force refers to the amount of pressure applied to push the material through the nozzle during printing. Maintaining a consistent extrusion force is crucial for ensuring that the material flows at the correct rate and with the right thickness, which is vital for achieving precise and accurate prints.

Fluctuations in extrusion force can lead to defects, such as over-extrusion (where too much material is deposited) or under-extrusion (where insufficient material is deposited), both of which negatively affect print quality. By stabilizing the extrusion force, the material is deposited evenly, layer by layer, ensuring uniformity and preventing defects like gaps, misalignment, or surface irregularities. This consistency is especially important when printing with high-resolution or multi-material designs, where small variations in extrusion force can lead to noticeable errors in the printed object. Tian et al.

(2024) highlighted that precise control over extrusion force not only reduces defects but also enables the printing of finer details and more intricate structures, ultimately enhancing the overall quality of the printed food product.

4.9. Printability Challenges

The printability of materials in 3D Food Printing (3DFP) is shaped by critical factors such as structural stability, material consistency, and production scalability, all of which directly influence the quality, efficiency, and feasibility of the printed products. Structural instability often arises when printed layers fail to maintain their shape or support subsequent layers, particularly in complex or tall structures, due to suboptimal rheological properties like inadequate yield stress or excessive fluidity (Kılınç & Kılınç, 2024).

Material inconsistencies, including variations in viscosity, particle size, and moisture content, further exacerbate these issues, leading to defects such as gaps, uneven surfaces, or delamination between layers, and complicating parameter standardization across production batches. Additionally, scaling up 3DFP for mass production faces hurdles such as prolonged printing times, high material consumption, and challenges in maintaining uniform quality, all of which limit its commercial viability, especially for intricate designs that require precision (Kılınç & Kılınç, 2024).

4.10. Printability Solutions

To address the challenges of printability in 3D Food Printing (3DFP), researchers have developed innovative strategies and material formulations to optimize the printing process and ensure successful outcomes. Advanced rheology modifiers, such as hydrocolloids and gelling agents, improve the flow and deformation behavior of materials, enhancing yield stress, viscosity, and shear-thinning properties. These modifiers, including xanthan gum and alginate, ensure smooth extrusion and shape retention post-deposition, contributing to structural stability without sacrificing print resolution (Kokane et al., 2024).

4.11. Integration of AI in 3DFP

The integration of Artificial Intelligence (AI) in 3D Food Printing (3DFP) has significantly advanced the technology by enabling real-time monitoring, adaptive manufacturing, and highly customizable production processes. Burke (2024) emphasized AI's transformative role in minimizing production time and facilitating the personalization of intricate food designs, aligning with the growing consumer demand for unique and functional food products.

AI-Driven Monitoring Systems: AI-powered monitoring systems leverage advanced algorithms to analyze real-time data from sensors and cameras embedded within 3DFP devices. Tian et al. (2024) demonstrated how these systems detect anomalies such as layer misalignment, irregular material flow, or temperature fluctuations during the printing process. By identifying deviations early, these systems enable automatic adjustments, ensuring consistent output quality and reducing material wastage. High-resolution imaging and machine learning (ML) techniques further enhance defect detection, allowing predictive maintenance and operational efficiency. AI-Augmented Additive Manufacturing: The integration of AI in additive manufacturing facilitates the optimization of design and printing parameters, enabling the production of highly intricate and functional food structures. Wang et al. (2024) described how AI algorithms, including deep learning models, predict the ideal combinations of layer thickness, extrusion force, and deposition speed based on material properties. This capability allows for the creation of complex geometries and multi-material constructs, such as hybrid textures or embedded bioactive ingredients, without compromising structural stability or aesthetic quality.

Closed-Loop 3D Printing: Closed-loop 3DFP systems represent a critical advancement in maintaining precision and adaptability for complex prints. These systems rely on real-time feedback loops where AI continuously adjusts parameters like extrusion speed, nozzle temperature, and layer height based on sensor inputs. Alghamdy et al. (2024) highlighted the role of closed-loop mechanisms in achieving high-resolution prints by dynamically correcting errors during production. For example, adaptive recalibration of material flow in response to viscosity fluctuations ensures uniform deposition, enhancing both scalability and repeatability. By integrating AI at multiple stages of the 3DFP workflow, the technology has achieved remarkable improvements in precision, efficiency, and customization, laying a robust foundation for future innovations in food manufacturing.

4.12. Advanced Innovations in 3D and 4D Printing

Recent advancements in 3D and 4D printing have revolutionized food production and biomedical engineering by introducing stimuli-responsive materials and multifunctional designs. These technologies enable unprecedented customization and functionality, as demonstrated by Wang et al. (2024), who emphasized their role in creating adaptive and interactive products tailored to evolving consumer and medical demands.

4D Printing and Time-Responsive Food Products: 4D printing builds on 3D printing by incorporating dynamic elements that allow printed structures to change their shape, properties, or functionality over time in response to external stimuli, such as temperature, pH, or moisture. Koirala et al. (2023) demonstrated its application in food printing, where stimuli-responsive hydrocolloids and biopolymers are used to create morphing food products.

For instance, a flat pasta sheet printed with anisotropic swelling agents can transform into a pre-designed 3D shape when boiled. This innovation not only enhances the aesthetic appeal and functionality of food products but also improves logistics by reducing storage space requirements, as flat-pack items can morph into complex structures during preparation.

4.13. AI-Powered Workflows in 3DFP

Nutritional Needs Prediction: Machine learning (ML) models analyze patterns in dietary intake and physiological responses to predict individual nutritional needs. Varghese et al. (2024) demonstrated how advanced ML algorithms use supervised and unsupervised learning to identify nutrient deficiencies, caloric imbalances, or dietary excesses. These predictions guide the formulation of 3DFP materials, such as bioactive inks enriched with specific vitamins, minerals, or macronutrients, ensuring that meals are not only personalized but also nutritionally comprehensive.

Optimized 3D-Printed Meal Generation: The culmination of AI-powered workflows is the generation of optimized 3D-printed meals that meet both functional and aesthetic criteria. Burke (2024) detailed how AI augments the design and printing stages, enabling intricate food structures that enhance sensory appeal and portion control. Algorithms optimize parameters such as extrusion speed, material composition, and layer thickness to create meals with consistent texture, taste, and appearance. For example, AI can adjust printing techniques to ensure soft food textures suitable for geriatric patients while preserving visual appeal to promote appetite stimulation.

Table 3 synthesizes recent research (2023–2024) on 3D and 4D food printing, highlighting critical advancements such as material innovations, printability optimization, and functional ingredient integration. The comparison emphasizes how artificial intelligence (AI) is increasingly pivotal to enhancing formulation precision, structural design, customization, and future smart food development. Cross-disciplinary insights, including nanotechnology, bioprinting, and commercial strategies, collectively signal a rapidly evolving landscape where AI technologies are central to unlocking new frontiers in food innovation.

Table 3: Comparative Analysis: Key Advances and AI-Driven Innovations in 3D and 4D Food Printing.

Reference	Key Findings	Comparison/Contribution to AI-Driven 3D Food Printing
Agarwal et al. (2024)	3D printing evolving with nanomaterials towards 4D printing.	Highlights futuristic materials integration for adaptive food printing.
Alghamdy et al. (2024)	Design features significantly impact 3D food printability.	Focus on AI optimization to enhance structural fidelity.
Burke (2024)	Reviews gastronomic evolution of 3D printed foods (2013–2024).	Provides historical context and identifies future trends.
Calton et al. (2023)	Paste formulation affects fiber alignment and texture in meat alternatives.	Emphasizes formulation precision aided by AI modeling.
Chen et al. (2024)	Multimaterial 3D/4D bioprinting for tissue engineering.	Cross-disciplinary insights into multi-material control for food textures.
de Farias et al. (2024)	Bibliometric mapping of Pickering emulsions in 3D food printing.	Shows rising interest in stabilizing emulsions for better printability.
Derossi et al. (2023)	3D printing accelerates food product prototyping.	Supports AI use in rapid prototyping of innovative foods.
Gu et al. (2023)	Wax-based emulsion gels' performance varies by crystal distribution.	Highlight ingredient-level optimization needed for better AI predictive models.
Kalogeropoulou et al. (2024)	4D printed biomaterials adapt shape over time.	Inspires dynamic, smart food products evolving post-printing.
Kılınç and Kılınç (2024)	Comprehensive review on current 3D food printing innovations.	Provides a state-of-the-art overview that guides AI integration.
Koirala et al. (2023)	Mechanisms of shape morphing foods discussed.	Offers mechanical transformation strategies for 4D food printing.
Kokane et al. (2024)	Bioactive ingredients can enhance 4D food health benefits.	Points to personalized nutrition via AI-driven ingredient selection.
Li et al. (2024)	Ferulic acid impacts structural and digestion properties of 3D-printed rice starch.	Encourages functional ingredient incorporation managed via AI.
Meijers and Han (2024)	Proposes a 3D Food Printing Pyramid of Gastronomy.	Suggests structured research models that AI systems can automate.
Nopparat and Motte (2023)	Business models in 3D food printing industry analyzed.	Shows commercial viability enhanced by AI-driven customization.
Sadraei and Naghib (2024)	Stimuli-responsive hydrogels for localized drug delivery via 4D printing.	Parallels smart food systems are responsive to environmental triggers.

Sajjad et al. (2024)	Overview of 4D printing and smart materials.	Underlines materials' role in future AI-controlled food designs.
Tian et al. (2024)	Single nozzle multimaterial ink printing optimization.	Boosts printing fidelity through AI-controlled multi-ingredient coordination.
Varghese et al. (2024)	Broad concepts and applications of 3D food printing.	Establishes foundational knowledge for AI expansion.
M. Wang et al. (2024)	Scientometric analysis on 3D food printing research.	Identifies knowledge gaps where AI-driven research can expand.
N. Wang et al. (2024)	Key factors and strategies for optimizing 4D food printing.	AI can automate optimization across multiple variables (time, temp, structure).
X. Wang et al. (2024)	Internal structural design influences nutrition post-printing.	AI models can predict post-processing nutritional outcomes.
Yang et al. (2024)	Nanocellulose aerogel printing for acoustic materials.	Suggests sustainable material potential for future edible structures.
Yarali et al. (2024)	Biomedical 4D printing applications.	Demonstrates high-level precision applicable to future food printing systems.

5. Discussion and Conclusions

The review explores the integration of machine learning (ML) and artificial intelligence (AI) in advancing 3D food printing (3DFP), focusing on optimization, customization, and overcoming technical challenges. ML algorithms like reinforcement learning and deep learning have been pivotal in improving design and fabrication, enabling food products with customized shapes and enhanced nutritional profiles (Li et al., 2024; Tian et al., 2024). However, challenges remain, particularly in ink printability issues such as viscosity and extrusion behavior, which affect the consistency and structural fidelity of printed foods. The integration of AI-driven systems faces difficulties in accurate data processing for optimizing food properties (Wang et al., 2024) (Kokane et al., 2024). Beyond production efficiency, AI and 3DFP hold transformative potential for personalized nutrition and healthcare, allowing tailored food production based on individual health needs, thereby advancing medical food generation and tissue engineering (Chen et al., 2024). AI-powered workflows promise more precise and efficient manufacturing processes (Agarwal et al., 2024). The review bridges AI and food printing technologies, emphasizing the need for sustainable, customized food systems by addressing ink optimization and AI integration challenges.

The systematic review, focusing on studies from 2023 to 2024, included technological advancements, application-based innovations, and future directions. Key areas included the use of ML algorithms to enhance print parameter optimization and material behavior in 3DFP. Practical applications showed 3DFP's versatility across food production, tissue engineering, and personalized meal development. The emergence of 4D printing, using stimuli-responsive materials for medical applications like vascular tissue engineering, was also explored. AI's role is further demonstrated through AI-driven monitoring systems that employ computer vision and real-time analytics to enhance precision and correct errors during printing (Wang et al., 2024) (Agarwal et al., 2024). These systems also enable the personalization of food products based on dietary or medical requirements (Burke, 2024; Varghese et al., 2024). Moreover, 4D printing introduces shape-shifting functionalities that extend into biomedical fields (Kalogeropoulou et al., 2024; Sadraei & Naghib, 2024). Addressing printability and material consistency is critical, with advancements in rheological property studies and machine learning-driven ink formulation enhancing the precision and scalability of 3DFP (Gu et al., 2023; Tian et al., 2024). In conclusion, AI and ML integration into 3DFP revolutionizes food production, fostering advancements in gastronomy, healthcare, and sustainability. Future research should focus on deeper AI integration, optimization of biocompatible materials, and expansion into diverse applications to unlock the full potential of these technologies (Meijers & Han, 2024; Yang et al., 2024).

5.1. Recommendations

Optimize Material Properties in 3DFP: To enhance the efficiency and quality of 3D food printing (3DFP), optimizing the material properties of food inks is crucial. Key aspects include improving ink viscosity and shear-thinning behavior characteristics that enable smooth extrusion and maintain structural stability during and after the printing process. This ensures precision in creating complex designs while avoiding issues like sagging or collapse (Alghamdy et al., 2024; Gu et al., 2023). Another avenue for improvement involves the incorporation of bioactive ingredients into printable materials. These ingredients, such as probiotics, vitamins, and functional compounds, can boost the nutritional value of 3D-printed foods. By addressing the needs of health-conscious consumers, this innovation aligns with trends toward personalized nutrition and dietary interventions (Kokane et al., 2024).

Enhance AI Integration: The integration of artificial intelligence (AI) in 3DFP can significantly improve the precision and adaptability of the process. AI-augmented additive manufacturing systems can provide real-time monitoring of critical factors such as extrusion force and print accuracy. These systems also enable error correction during printing, reducing material wastage and improving efficiency (Wang et al., 2024) (Tian et al., 2024). Furthermore, the use of reinforcement learning and deep learning algorithms can enhance predictive modeling for optimized meal generation. For instance, AI can analyze individual patient data to tailor food textures, nutrient compositions, and flavors, offering customized solutions for medical or dietary needs (Sadraei & Naghib, 2024; Yang et al., 2024).

Explore Advanced Printing Techniques: The adoption of 4D printing technologies in food production is another promising direction. Unlike traditional 3D printing, 4D printing incorporates materials that can respond to external stimuli, such as temperature, pH, or moisture. This adaptability has significant potential in areas like vascular tissue engineering and stimuli-responsive foods, where functionality and design need to evolve over time (Kalogeropoulou et al., 2024; Sajjad et al., 2024). For instance, foods printed with 4D techniques could change shape or texture when cooked or consumed, offering novel culinary experiences and practical applications in healthcare and sustainability. Interdisciplinary Collaboration: To fully realize the potential of 3DFP, fostering interdisciplinary collaboration is essential. Material scientists, AI developers, and food technologists must work together to create customized food products that cater to diverse consumer demands. By pooling expertise, these professionals can address challenges such as improving material printability, enhancing nutritional content, and integrating advanced AI-driven solutions into the manufacturing process (Wang et al., 2024) (Meijers & Han, 2024). Collaborative efforts can also accelerate innovation, bringing tailored and sustainable 3D-printed foods to a broader market.

5.2. Implications of the Review

Scientific Advancements: The integration of artificial intelligence (AI) into 3D food printing (3DFP) has the potential to revolutionize personalized nutrition and dietary interventions. AI algorithms can analyze patient data, including chronic conditions and nutritional needs, to create tailored meals that meet specific dietary requirements. This approach is particularly beneficial for patients managing conditions such as diabetes, cardiovascular disease, or food allergies, enabling precision in nutrient intake and portion control (Wang et al., 2024) (Varghese et al., 2024). Beyond AI, advancements in material science play a pivotal role in the evolution of 3DFP. The incorporation of nanomaterials into 4D printing paves the way for sustainable and functional food production, where printed foods can exhibit enhanced properties such as extended shelf life, improved texture, and dynamic response to environmental stimuli (Agarwal et al., 2024; Burke, 2024).

Industrial Applications: The development of enhanced printability solutions for 3DFP is driving its adoption across various industries. In settings such as restaurants, hospitals, and schools, technology allows for the preparation of customized, nutritionally balanced meals on demand. This capability not only improves meal customization but also addresses broader challenges like reducing food waste by using precise ingredient measurements and repurposing surplus materials (Nopparat & Motte, 2023). Additionally, 3DFP offers the potential for streamlined operations in healthcare institutions, where tailored meals can be printed to support specific medical diets, further enhancing patient care (de Farias et al., 2024). Consumer Benefits: From a consumer perspective, customized food printing is transformative in addressing dietary needs and restrictions. It enables the creation of meals that cater to individual preferences and allergies, ensuring both safety and satisfaction. Furthermore, the ability to produce aesthetically appealing foods makes 3DFP a valuable tool for enhancing the dining experience, particularly for younger audiences or individuals with feeding challenges.

In healthcare, technology has therapeutic applications, such as producing nutrient-rich, easy-to-swallow meals for patients with dysphagia or other eating difficulties (Chen et al., 2024; Meijers & Han, 2024). The combination of personalization, functionality, and visual appeal positions 3DFP as a game-changing innovation in modern food production and consumption. Policy Implications: The integration of AI-driven 3D food printing (3DFP) requires strategic policy interventions to optimize benefits and manage risks. Governments should fund domestic R&D and encourage public-private partnerships for sustainable innovation (Agarwal et al., 2024; Kokane et al., 2024). Regulatory frameworks must ensure food safety, clear labeling (Burke, 2024; Kılınç & Kılınç, 2024), and workforce reskilling to counter job displacement (Nopparat & Motte, 2023). Emphasis on locally sourced, biodegradable materials and energy efficiency is critical (Calton et al., 2023; Yang et al., 2024), along with cybersecurity and IP protection (Alghamdy et al., 2024; Sajjad et al., 2024). Consumer education enhances trust (Wang et al., 2024) (Varghese et al., 2024). Risks include supply chain vulnerabilities (Chen et al., 2024), job losses (Nopparat & Motte, 2023), nutritional concerns (Kokane et al., 2024; Li et al., 2024), cultural disruptions (Burke, 2024), and environmental trade-offs (Yang et al., 2024), all requiring proactive, balanced policy responses.

5.3. Limitations

Technological Constraints: The adoption of 3D food printing (3DFP) on a large scale faces significant technological barriers. One key limitation is the scarcity of food-grade 3DFP printers compatible with AI integration. Many existing printers lack the precision and real-time adaptability required for complex tasks like nutrient customization and structural optimization, making them unsuitable for industrial-scale applications (Kılınç & Kılınç, 2024; Tian et al., 2024).

Furthermore, maintaining the structural integrity and fidelity of intricate designs remains a challenge. Complex food structures often collapse or lose definition during or after the printing process due to limitations in material properties or printer accuracy (Wang et al., 2024) (Gu et al., 2023). These issues highlight the need for advanced printer technology and materials tailored for 3DFP.

Data and AI Challenges: The development of AI-driven systems for 3DFP is hindered by the lack of comprehensive datasets necessary for training accurate monitoring and predictive models. AI systems rely heavily on robust data to address challenges such as printability issues, extrusion force optimization, and error correction.

However, the food printing domain suffers from limited standardized datasets, reducing the effectiveness of machine learning models in predicting outcomes or adapting to diverse material properties (Sajjad et al., 2024; Yang et al., 2024). This gap underscores the need for interdisciplinary collaboration to establish data-sharing platforms and datasets tailored for 3DFP.

Regulatory Hurdles: The commercialization of 3D-printed foods is further complicated by inconsistent regulatory frameworks across different countries. While some regions have established clear guidelines for food safety and quality, others lack standardized protocols for assessing the nutritional, structural, and safety aspects of 3D-printed foods. This disparity creates uncertainty for manufacturers and slows down market entry and adoption (Burke, 2024; Nopparat & Motte, 2023). Harmonizing global standards and addressing food safety concerns are essential steps for accelerating the widespread use of 3DFP technology.

Publication Bias: Publication bias is a major methodological limitation in AI-driven 3D food printing research. Many studies (Wang et al., 2024) (Agarwal et al., 2024; Burke, 2024) emphasize positive outcomes, creating a skewed view of the field's maturity by underrepresenting failures, technical barriers, cost challenges, and consumer acceptance issues.

Bibliometric analyses (Wang et al., 2024) (de Farias et al., 2024) further amplify this bias by relying on published successes. Consequently, the field's progress may seem more advanced than it is, risking overoptimistic interpretations. Addressing publication bias is essential to achieving a realistic and balanced understanding of 3D food printing technologies.

5.4. Future Research Directions

Material Innovation: Advancing 3D food printing (3DFP) requires the development of multi-functional food inks that cater to both consumer preferences and industrial requirements. Emphasis should be placed on enhancing the shear-thinning properties of these inks, which improve extrusion efficiency and maintain the structural stability of printed foods. Additionally, ensuring biocompatibility is crucial for applications in personalized nutrition and medical-grade foods (Calton et al., 2023; Li et al., 2024). Such innovations will enable the creation of diverse food textures, shapes, and nutritional profiles, meeting the growing demand for tailored dietary solutions.

AI Enhancement: Integrating AI into 3DFP workflows offers the potential to achieve autonomous optimization during the printing process. Closed-loop systems enhanced by AI-driven monitoring can track key parameters like extrusion force and print accuracy in real-time. These systems allow for error correction on the fly, minimizing material wastage and improving overall efficiency (Tian et al., 2024; Varghese et al., 2024). By employing advanced algorithms, printers can also adjust to material inconsistencies, ensuring consistent quality across diverse food inks.

Expanding 4D Printing: The incorporation of 4D printing where printed objects can change shape or function in response to external stimuli represents a transformative leap in both food and biomedical applications. For instance, stimuli-responsive designs can be utilized in creating functional foods that release nutrients based on digestion phases or environmental triggers. Similarly, 4D-printed structures hold promises in drug delivery systems and tissue engineering, showcasing the interdisciplinary potential of this technology (Kalogeropoulou et al., 2024; Sadraei & Naghib, 2024).

Sustainability and Scalability: Sustainability is a critical focus for the future of 3DFP. Researchers are exploring ways to reduce environmental impacts by incorporating sustainable materials and minimizing waste during production. Additionally, scaling these technologies to industrial levels requires innovations that balance cost-effectiveness with environmental responsibility, such as using alternative energy sources and biodegradable components (Agarwal et al., 2024; Yang et al., 2024). These steps will ensure that 3DFP contributes to global efforts in promoting sustainable practices.

By combining advancements in material science, AI, and sustainability, 3D and 4D food printing technologies are poised to revolutionize personalized nutrition, healthcare, and sustainable practices. These innovations will not only reshape the food industry but also expand its reach into biomedicine, offering novel solutions to complex challenges.

5.5. Declarations

Ethics Approval and Consent to Participate

Not applicable

Consent for Publication

Not applicable

Availability of Data and Materials

The study is a narrative review and does not involve the collection or analysis of original data from participants. All information and insights presented in the study are derived from existing literature, publicly available sources, and secondary data obtained from previous research. As such, no new datasets were generated or analyzed during the study.

Competing Interests

I, as the sole author and the corresponding author of the article, declare that I have no competing financial or personal interests that could have influenced the work reported. The review article was conducted independently, with no external influences, funding, or affiliations that could have impacted the findings or interpretations presented.

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I, the sole author and the corresponding author have made substantial contributions to the conception, study, and writing of the review article. The author reviewed, edited, and approved the final manuscript, ensuring it met academic standards and provided a balanced, evidence-based discussion. The author confirms that the article represents original work and bears full accountability for the content presented in the publication.

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