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Rheological analysis in food processing: factors, applications, and future outlooks with machine learning integration

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Food rheology serves as a critical tool for characterizing the flow and deformation properties of food, which directly impact its texture, taste, stability, and overall quality. The complex production environments and rapidly evolving market demands necessitate the integration of rheology with machine learning (ML) to accurately and effectively characterize and optimize the rheological properties of food. This review, with a focus on machine learning, examines texture analysis, including both large deformation rheology measurements, and small deformation rheology. It summarizes the factors influencing food rheology, emphasizing the interactions between key food components that affect rheological properties and the rheological characteristics of complex food systems. Furthermore, this review explores the detailed applications of combining rheology and machine learning in the food industry, as well as the associated challenges and future outlooks. ML has demonstrated significant efficacy in predicting and analyzing food rheology, despite the challenges posed by large datasets and intricate production conditions. The integration of ML with food rheology facilitates the analysis of food flow and deformation, optimization of product formulations, monitoring of production processes, and execution of sensory analysis. While ML-based approaches to rheology have advanced considerably in the context of food processing and quality assurance, substantial potential for further development remains.

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1. Introduction

Food rheology is concerned with the flow, deformation, and mechanical behavior of food substances throughout

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processing, storage, transportation, and consumption.[1] This discipline encompasses a broad spectrum of factors, including the physical properties, texture, and taste of food ingredients.[2,3]

From a measurement standpoint, food rheology is commonly characterized through both small-deformation tests (*e.g.*, shear and oscillatory measurements that evaluate viscoelastic responses), as well as large-deformation techniques, like texture analysis, which assess structural resistance under practical processing and consumption conditions. Food production processes and quality control have increasingly introduced complex challenges due to the rapid expansion of the global food industry and the diversification of consumer preferences. Although traditional rheological methods have facilitated theoretical and experimental advancements, they are often inadequate for addressing the dynamic nature of production environments and evolving market demands due to their reliance on physical experimentation and complex mathematical modeling. Consequently, there is a need for precise and

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efficient characterization and optimization of food rheological properties that are crucial for fostering innovation in the food industry and enhancing product quality.

The recent rapid advancements in information technology have established machine learning (ML) as a pivotal tool for addressing challenges in food rheology. ML, which involves the automatic learning and optimization of models from data, is adept at managing complex nonlinear relationships and identifying latent patterns and trends within diverse experimental datasets. Therefore, ML can integrate various rheological data types, such as small-amplitude oscillation spectra collected by rheometers and large-deformation force-time/force-displacement sequences acquired from texture analyzers, to construct multimodal models that associate mechanical characteristics with sensory properties and processing performance. Compared with traditional methods, ML offers flexibly and efficient means of predicting and analyzing food rheology data without requiring deep knowledge of complex physical mechanisms.[1]

The integration of ML technology in food rheology has many applications. ML provides a data-driven approach for the development of food rheological models, facilitating researchers to understand food flow and deformation, and thereby reducing dependence on traditional physical equations.[4] ML can also be used to optimize and design food formulations, as well as to elucidate the relationship between ingredients and rheological properties utilizing historical data.[5] Therefore, ML can be used to achieve intelligent optimal ingredient ratios to fulfill the desired texture and sensory attributes of a product.[6] Such optimization commonly relies on the complementary use of small-deformation rheological parameters, which describe material structure and stability, and large-deformation texture metrics that are more closely associated with consumer sensory perception. Moreover, ML is instrumental in production processes by enabling real-time monitoring and adjustments, thereby ensuring consistent food rheological properties and stable quality. The combination of ML with rheology in sensory analysis can enhance the prediction of sensory attributes, significantly supporting product innovation. However, ML encounters several challenges, including data complexity and limited model interpretability, which necessitate ongoing research and enhancement. These challenges are further amplified by the coexistence of heterogeneous data derived from small- and large-deformation rheological measurements, highlighting the need for standardized protocols and feature representations.

The application of ML in food rheology is poised for substantial enhancement as technological advancements continue. The precision, real-time analysis, and efficiency of ML applications are expected to improve significantly due to ongoing improvements in data collection methodologies, sensor technologies, and computational power, thereby exerting a profound impact on food rheology. This paper provides a comprehensive overview of the existing conditions, developmental trends, and challenges related to ML applications in food rheology. Furthermore, ML in the modeling of rheological behavior extends to formulation design, optimization of production processes, and sensory analysis. Therefore, this study can provide a valuable guide for academic institutions, the food industry, and technology developers, thereby facilitating further advancement and industrial applications in food rheology research.

2. Factors of food rheology

Food rheology is primarily concerned with the study of the flow, deformation, and mechanical behavior of food materials under external forces, encompassing both liquids and structured solid or semi-solid systems. Fundamentaly, food rheology seeks to characterize the material responses to deformation across different length and strain scales, including small-deformation behavior that probes viscoelastic structure and large-deformation responses that govern fracture, yielding, and texture during processing and consumption. These mechanical responses arise from the complex composition and hierarchical structure of food matrices and manifest as flow, deformation, and failure under applied stresses, which are critical for understanding food behavior during both processing, storage, and oral handling. Consequently, rheological properties play a central role in determining food texture and sensory perception.

From a measurement perspective, rheological characterization of foods can be broadly divided into small-deformation and large-deformation approaches. Small-deformation rheology is commonly performed using rheometers that operate under controlled stress or strain, providing quantitative parameters, such as viscosity, yield stress, and viscoelastic moduli. As shown in Fig. 1, based on their measurement principles, conventional rheometers can be classified into shear rheometers (rotational rheometer, oscillatory rheometer, and capillary rheometer),[7] tensile rheometers (Münstedt tensile rheometer, filament stretching rheometer, and Sentmanat extensional rheometer),[8] and micro/special rheometers (microrheometer,[9] interfacial rheometer,[10] and ultrasonic rheometer[11]). Within the torque-based group, one can further distinguish rotational (continuous shear) rheometers and oscillatory (dynamic) rheometers, which are specialized for more detailed probing of a sample's shear flow and viscoelastic behavior under controlled torque or stress conditions.

In contrast, large-deformation rheological behavior is commonly assessed through texture analysis, particularly for solid and semi-solid foods. Texture analyzers are employed to apply various deformations, including compressive, tensile, penetration, cutting, bending, or extrusion, which result in force–time or force–displacement profiles. From these profiles, parameters such as hardness, firmness, cohesiveness, springiness, chewiness, adhesiveness, and fracture force are derived.[12] These measurements capture non-linear and often destructive mechanical responses that are directly relevant to food handling, processing performance, and consumer sensory perception. In many food systems, particularly gels, doughs, and multiphase composites, small-deformation rheological parameters describe intrinsic material structure and stability, while large-deformation texture metrics reflect functional

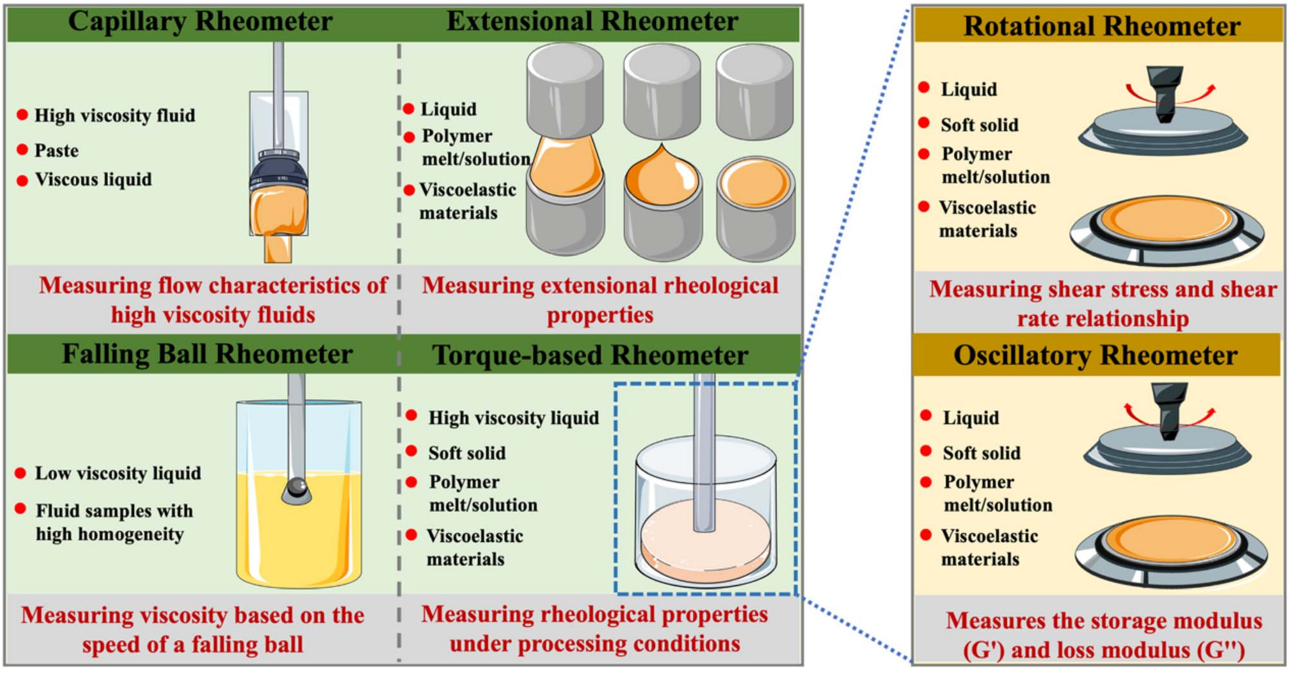

Fig. 1 Types of rheometers.

performance under practical use conditions. Consequently, both measurement scales offer complementary insights into food rheology, and the exclusion of either would result in an incomplete characterization of the mechanical behavior of food.

2.1 Key food components influencing rheology

Water is a vital part of food and significantly affects food safety, quality, and physical properties. Water can improve the fluidity of food systems by minimizing internal friction, thereby reducing viscosity and altering viscoelastic responses under small-deformation conditions. The state of water, whether free or bound, influences the viscosity and elasticity of these systems. These effects are also reflected in large-deformation behavior, where water content governs flexibility, fracture resistance, and textural attributes during compression or extrusion. Interactions between water and macromolecules, such as proteins and polysaccharides, lead to changes in electron cloud distribution, facilitating the formation of hydrogen bonds. These interactions contribute to the formation and stabilization of the spatial configurations of biopolymers, affecting the engineering characteristics of food. Water acts as a plasticizer in low-moisture foods, such as biscuits and candies, reducing intermolecular forces and boosting flexibility, which is manifested as reduced brittleness under large-deformation loading. Suitable water content can reduce brittleness in starch-based products, thus preventing cracking during extrusion. Furthermore, water stimulates to dissolve gluten proteins and starch molecules in dough, thus improving stretchability, viscoelasticity, and flowability of medium-moisture foods.[13] In high-moisture foods like soups and beverages, water serves as the main fluid, with its viscosity, density, and intermolecular interactions greatly influencing the flow and texture of food.[14]

The impact of proteins on the rheological properties of food is predominantly governed by their molecular structure and physicochemical characteristics.[15] Proteins, as complex biopolymers, influence the rheology of food matrices under both small-deformation conditions (*e.g.*, viscoelasticity) and large-deformation conditions (*e.g.*, gel firmness and fracture behavior). The amino acid sequences dictate intermolecular interaction strength. Proteins that are abundant in hydrophobic amino acids tend to form dense network structures, thereby enhancing the system's elasticity.[16] Proteins can aggregate into gels, fibers, or particles, which substantially alter the viscoelasticity and texture of food.[17] These aggregation processes determine not only the linear viscoelastic moduli observed under small deformations but also the resistance to compression and breakdown associated with food texture. Moreover, the distinct spatial configurations of proteins confer unique rheological properties to a system. For protein-based gels, texture profile analysis (TPA) is frequently employed to quantify firmness, cohesiveness, and chewiness, which complement small-amplitude oscillatory measurements in describing gel structure and mechanical integrity. However, denaturation modifies the native conformation of a protein, thereby affecting its fluidity or viscosity. Protein denaturation frequently occurs during food processing and substantially alters the rheological properties of food. Heat treatment, for instance, induces protein unfolding, exposing additional reactive sites and promoting the formation of strong intermolecular networks. Variations in pH can also affect the charge distribution and solubility for proteins, thereby influencing viscosity. In dairy products, casein aggregates to form gel structures when pH approaches the isoelectric point, inducing a distinct texture and mouthfeel.

For lipids, the effect on the rheological properties of food is primarily determined by their state, physical characteristics, and structure. Lipids serve as a fundamental source of energy and a key contributor to flavor, play a crucial role in regulating the rheological properties of food products. The physical state of lipids has a direct impact on the flow of food under small deformation, as well as on hardness and plasticity under conditions of large-deformation mechanical loading. Fluid lipids, have reduced thickness, thus promoting the movement of food. Fluid oils reduce the adhesive properties of loaf mixtures, thereby facilitating easier handling and processing. Solid lipids provide structural support, facilitating the hardness and moldability of food, which are key contributors to perceived texture during mastication. In addition, smaller, more evenly scattered lipid droplets improve the steadiness and mouthfeel of food frameworks an increased concentration of fat globules increases viscosity, thereby enhancing resistance to flow. For example, high-fat coconut milk exhibits greater viscosity compared to its low-fat variant.[18] The crystalline structures of lipids, specifically the α, β′, and β form, significantly influence the texture and processability of food. Particularly, the β′-form has superior plasticity and workability, imparting a soft and smooth texture to various products, such as margarine.[19] Furthermore, the rate of crystallization and the size of lipid crystals significantly affect the hardness and sensory attributes of food. Controlled crystallization in chocolate production results in uniform microcrystals, obtaining the desired snap and a smooth melting sensation.[20]

Polysaccharides, as biomacromolecules, substantially impact the rheological properties of food across various deformation scales, thereby affecting mouthfeel, quality, and stability. The structural complexity of polysaccharides is a key determinant of their rheological properties. Polysaccharides with high molecular weight enhance the viscosity of systems due to their extended molecular chains, which occupy a larger volume in solution, thereby increasing flow resistance.[21] Moreover, amylose, linear polysaccharides, exhibit high crystallinity and elasticity, whereas amylopectin, branched polysaccharides, readily form viscous solutions due to their less ordered structure. Rigid-chain polysaccharides contribute to the increased viscosity in solutions, while flexible-chain polysaccharides tend to decrease viscosity.[22] Charged polysaccharides can form gels through ionic interactions, thereby imparting specific rheological characteristics to food systems. Additionally, the concentration of polysaccharides plays a crucial role in determining their rheological behavior. Low-concentrated polysaccharides display exhibit pseudoplastic behavior, characterized by a reduction in viscosity with an increasing shear rate. At higher concentrations, these systems exhibit pronounced resistance to large deformation, forming gels or thick pastes with distinct textural attributes. This property is widely utilized in dairy beverages to enhance smoothness.[23,24] Conversely, high-concentrated polysaccharide solutions form elastic gels or thick liquids. In these systems, large-deformation tests based on texture analysis are widely used to assess gel strength, fracture behavior, and cohesiveness, providing parameters directly related to consumer perception. For instance, gelatinized starch develops a network structure at high concentrations, contributing to the thick texture of sauces.[25] Processing conditions, such as temperature, pH, and ionic strength, also have a significant impact on the rheological properties of polysaccharides. Heating can induce gelatinization in starch, resulting in the formation of viscous fluids or gels.[26] However, gelatinized starch may undergo retrogradation upon cooling, thereby impacting the texture and stability of food.[27] Pectin molecules lose their charges under acidic conditions, facilitating gel formation and affecting the viscosity of products such as jams and yogurt. Additionally, ions can promote polysaccharide gelation. For example, κ-carrageenan forms firm gels in the presence of potassium ions, making it suitable for puddings and jellies.[28]

In addition to water, polysaccharides, and lipids, low-molecular-weight compounds and hydrocolloids are crucial determinants of food texture across various systems. Low-molecular-weight compounds, such as sucrose, fructose, and rare sugars (a type of monosaccharide found in small amounts in nature and sugar alcohols), can significantly influence rheological properties not only by modifying solution viscosity and osmotic pressure but also by interacting with proteins or polysaccharides to regulate structural stability and mouthfeel. Meanwhile, various hydrocolloids, owing to their thickening, gelling, and stabilizing capacities, can markedly improve or control textural attributes in complex food matrices, thereby enhancing both sensory quality and processing performance. Thus, the formation and modulation of food texture and rheological behavior under both small- and large-deformation conditions are often the result of synergistic effects among multiple components, with low-molecular-weight compounds and hydrocolloids playing indispensable roles in this process. The effects of these components on the rheological properties of food are summarized in Table 1.

2.2 Interactions between components

The mechanisms of interaction among components are pivotal in determining rheological properties in food systems. These interactions significantly regulate the microstructure, stability, and quality of foods, thereby governing both their rheological behavior and the development of characteristic textural attributes. These interactions between components include physical and chemical mechanisms, which collectively influence the overall rheological behavior of food.

The interaction between water and proteins plays a central role in regulating protein conformation, network formation, and the resulting textural properties of food systems. Water serves as the solvent in protein solutions and affects protein structure and functionality. These interactions arise primarily from hydrogen bonding, electrostatic interactions, and hydrophobic effects, which collectively determine protein hydration, molecular mobility, and structural organization in aqueous environments.[38,39] The interaction of proteins with water

Table 1 Effects of components on the rheological properties of food

Food components	Rheological tests	Influence	References
Water	Frequency sweep, creep-recovery	Moisture content not cause significant changes in the dough frequency sweep parameters, but decreased moisture content reduced the creep-recovery index	29
Water	Frequency sweep	Adding water in stages helps improve the viscoelasticity of the dough	30
Casein	Shear rate ramp	The viscosity of whey protein-free milk increases with increasing casein concentration	31
Whey protein isolate	Shear rate ramp, frequency sweep	The presence of whey protein isolate reduced the apparent viscosity of milk protein concentrate paste. G' and G'' gradually decreased with increasing whey protein content	32
Xanthan gum	Shear rate ramp, frequency sweep	After adding xanthan gum, the 3D-printed cooked pork mince samples exhibited higher viscosity and a higher loss tangent (closer to viscous behavior)	33
κ-Carrageenan gum, xanthan gum, and Arabic gum	Shear rate ramp, frequency sweep	Adding κ-carrageenan gum and xanthan gum significantly improved the mechanical strength (yield stress and elasticity) and viscosity of the 3D printed ink samples; while adding Arabic gum showed the opposite effect	34
Chitosan	Shear rate ramp	Chitosan increased the apparent viscosity of corn starch	35
Konjac glucomannan	Shear rate ramp, frequency sweep	With the increase of konjac glucomannan addition, the storage modulus, loss modulus, and viscosity of the dough increased	36
Medium-chain triglyceride oil	Shear rate ramp	The viscosity of food-grade 3D ink gradually increased with increasing oil content	37

molecules in dairy products to form a homogeneous solution reduces viscosity and enhances fluidity.[40] Water molecules are involved in protein gelation processes under optimal conditions, influencing the elasticity and viscoelasticity of food. During protein denaturation and network formation, water acts as a filler within the three-dimensional structure, stabilizing the network and directly influencing gel compactness and firmness. Accordingly, texture-related parameters such as firmness and cohesiveness are commonly employed to assess evaluate the strength of protein–water networks in heat-induced protein gels. Niu *et al.*[41] demonstrated that soy proteins interact with water to form elastic gels after heating, where enhanced water retention promoted a denser gel network and higher gel firmness. This process is widely used in the production of plant-based meat. Changes in the environment can accelerate protein decomposition in water, changing food flow qualities. Heating promotes interaction between protein and water, causing unfolding and revealing extra responsive spots of protein. This interaction improves compactness between molecule networks, increasing thickness and stretchiness. Moreover, the water absorption capacity of proteins greatly affects the thickness and movement characteristics of food. Gluten proteins can absorb extensive water to form a highly stretch-flow network, giving them distinct expandability and processability. Conversely, whey proteins that exhibit a lower water absorption capacity tend to form solutions with reduced viscosity.[42] The quantity of water present substantially affects the structural and rheological properties of proteins in food. Restricted water amount in low-water food, such as cheese or jerky, limits protein movement, leading to low-movement solid forms. Meanwhile, proteins in high-water systems, such as broths or drinks, exhibit greater mobility, leading to increased molecular movement and reduced structural density.

The interaction between water and lipids primarily governs emulsion structure and fat crystallization behavior, thereby influencing mouthfeel, viscosity, and textural consistency of food products. In oil-in-water emulsion systems, water generally acts as the continuous phase, whereas the lipid is dispersed throughout. In water-dominated systems such as milk and ice cream, water serves as the continuous phase, encapsulating lipids to form a stable emulsion that contributes to a smooth texture, moderate viscosity, and suitable hardness of the final product. In ice cream systems, such effects of water–lipid interactions are commonly evaluated through measurements of hardness and ductility, which reflect emulsion stability and fat structuring.[43] The water-to-lipid ratio significantly affects the phase behavior and rheological properties of the system. Conversely, systems where water predominates, such as low-fat milk, exhibit reduced viscosity and enhanced fluidity. Whole milk demonstrates a greater viscosity compared to skim milk due to lipid, which increases resistance to flow.[44] In lipid-dominated systems such as butter and chocolate, the limited availability of water and lipid crystallization behavior result in plastic or yielding textures characterized by higher hardness and structural stability.[45] For chocolate, an optimal amount of water can stabilize lipid crystals, while excessive water may result in fat separation and an uneven texture.[46] Moreover, water and lipid contribute to the lubrication of dough. Water serves to decrease internal friction by establishing a fundamental level of lubrication, whereas lipid enhances this effect by filling the interstitial spaces between particles. This action reduces viscosity and enhances the extensibility of dough. The synergistic interaction between water and lipid in bread dough mitigates gluten network viscosity, while making the dough softer and improving its processing properties.[47] The interaction between water and lipid undergoes a dynamic transformation during the heating process, wherein liquid vaporization and lipid liquefaction significantly influence structural transitions and flow properties. Specifically, liquid vaporization enhances the hardness of baked products, whereas lipid liquefaction makes the products softer and smoother.

A prevalent common physical phenomenon in food systems is the interaction between water and polysaccharides, which plays a crucial role in the thickening, gelling, and stabilization of suspensions. Water and polysaccharides, including pectin, agar, and carrageenan, engage in interactions that result in the formation of a three-dimensional network structure, primarily facilitated by hydrogen bonding.[48] These interactions impart specific elasticity and texture to food products by forming hydrated polysaccharide networks with varying gel strength and fracture resistance. For instance, the gel strength and breaking behavior of pectin- or carrageenan-based systems are widely used to characterize the effectiveness of water–polysaccharide interactions in products like jams and desserts.[49] Low methoxyl pectin can form a gel in the presence of calcium ions and is commonly utilized in the production of various food items, such as jams and puddings. Furthermore, polysaccharide solutions exhibit non-Newtonian fluid characteristics, where their viscosity decreases with increasing in shear stress. The shear force partly breaks the interaction between liquid and complex sugar molecules, causing a more orderly setup of molecular chains and decreasing flow resistance. Environmental conditions, including temperature, pH, and ionic strength, significantly affect the interaction between water and polysaccharides. High temperatures can accelerate gelatinization of polysaccharides, increasing viscosity. However, cooling may lead to a regeneration effect, thereby impacting the textural stability of food products. In acidic environments, the diminished charge of pectin promotes gel formation, thereby influencing the texture of yogurt and jam.

Proteins interact with lipids primarily through adsorption at oil–water interfaces and incorporation into bulk matrices, thereby modulating emulsion stability and textural properties. Proteins function as emulsifiers, facilitating the stabilization of lipid droplets within emulsion systems such as milk, cream, and salad dressings.[50] Proteins form an elastic interfacial film by adsorbing at the oil–water interface, thereby preventing the aggregation of lipid molecules. The interaction between proteins and lipids in mayonnaise is essential for preserving the stability and creamy texture of the emulsion. Furthermore, proteins establish a three-dimensional gel network that encapsulates and stabilizes lipid components, thereby conferring elasticity and firmness. In meat products and cheese, thermally denatured proteins interact with lipids to reinforce the three-dimensional network, leading to increased firmness, cohesiveness, and improved mouthfeel.[51,52] These texture-related parameters are particularly significant in meat and cheese products, where protein–lipid interactions influence slicing behavior and oral processing characteristics. Moreover, proteins affect the solidification behavior of lipids, which can either promote or inhibit the formation of lipid crystals. Milk proteins interact with lipids in frozen foods, such as ice cream, to develop a stable and fine texture, preventing the formation of large lipid crystals.[53] Conversely, the interaction between proteins and crystallized lipid is diminished in butter, promoting the development of a homogeneous microcrystalline structure that enhances the desired firmness and spreadability. Furthermore, proteins engage in complex formation with lipids, wherein the lipids are partially encapsulated by proteins or interconnected *via* protein molecules. This intricate structure substantially augments the viscoelastic properties of the system. In yogurt, homogenized casein interacts with lipids to establish a dense matrix, which imparts a thick and smooth texture, thereby enhancing flow resistance.[54] The processing conditions, including homogenization, heating, and whipping, influence the interactions between proteins and lipids, thereby affecting the rheological properties. Heating induces protein denaturation, which enhances emulsification and fortifies the protein–lipid network.[55] The interactions between proteins and lipids can be either beneficial or detrimental, depending on the composition of the food. Proteins can stabilize lipids and increase rheological properties. Nevertheless, excessive lipid may disrupt the protein network, diminishing gel strength or elasticity. Therefore, a balanced ratio of protein to lipid is crucial for achieving the desired texture and rheological properties in product development.

The interaction between proteins and polysaccharides plays a crucial role in gelled and fermented food systems, as it governs network formation and texture development. Polysaccharide molecules enhance intermolecular connectivity and modify texture by forming hydrogen bonds or electrostatic interactions with polar groups, such as hydroxyl and carboxyl groups, on the surface of protein molecules.[56,57] Under acidic conditions, positively charged proteins form complexes with negatively charged polysaccharides such as pectin and carrageenan, resulting in increased viscosity and enhanced gel firmness.[58,59] Polysaccharides and proteins establish a flexible network structure under neutral conditions through hydrogen bonding and hydrophobic interactions, thereby enhancing rheological resistance.[60] The synergistic interaction between proteins and polysaccharides facilitates gel formation and improves elasticity and firmness. The synergistic interaction between whey protein and xanthan gum in yogurt leads to a denser network structure, resulting in improved consistency and higher resistance to deformation during storage.[61] Proteins and polysaccharides can form cross-linked structures *via* hydrogen bonding, resulting in a three-dimensional mesh network that stabilizes the texture and elasticity.[62] The interaction between proteins and polysaccharides in specific gel systems enhances gelation, resulting in the formation of a more robust gel structure.

Moreover, the interaction between lipids and polysaccharides influences the structure and texture of various foods, particularly in terms of flavor, stability, and uniformity. These interactions occur through mechanisms such as physical adsorption, intermolecular forces, and network embedding. Polysaccharide molecules can encapsulate lipids *via* adsorption, thereby enhancing emulsion stability and viscosity. The polar groups of polysaccharides are capable of forming hydrogen bonds with polar molecules on the lipid surface, while their hydrophobic regions interact with the nonpolar segments of lipid molecules. In gel systems, polysaccharides establish a three-dimensional network that entraps lipids, thereby enhancing elasticity and stability.[48] The incorporation of lipids with gelatin and xanthan gum can enhance the smoothness and textural consistency of ice cream.[63] Such lipid–polysaccharide interactions are prevalent in gel systems, where they contribute to maintaining a robust gel structure and elasticity.

In conclusion, the interplay among primary food constituents significantly influences the complex rheological properties through various mechanisms. These interactions, together with external factors such as concentration, temperature, and processing conditions, are pivotal in determining the structural integrity, stability, flavor, texture, appearance, and processing efficacy of food products. Consequently, understanding the interplay among food components is essential for controlling microstructure, tailoring textural attributes, and optimizing the rheological and sensory performance of food products.

2.3 Rheological signatures of complex foods

2.3.1 Dairy products. Rheology plays a critical role in the dairy industry, as the texture, mouthfeel, and stability of dairy products are closely associated with their rheological characteristics in Fig. 2. Rheological analysis facilitates the optimization of dairy product formulation and production processes, thereby enhancing product quality and consistency.

Rheology is an essential tool for managing the texture and sensory characteristics of dairy products, influencing properties such as smoothness, thickness, and firmness in items like yogurt, cream, and ice cream.[64,65] The textural properties of these products can be modulated by altering their rheological properties, particularly viscosity and elasticity, which directly determine perceived thickness and structural integrity. By precisely controlling viscosity, yield behavior, and viscoelasticity during processing, ice cream can be engineered to exhibit a smooth, creamy texture and controlled melting behavior during consumption.[66] Indeed, rheological measurements enable the regulation of fermentation by linking protein network development with macroscopic consistency and final textural attributes, thereby ensuring product uniformity.[67]

Rheological properties are integral to the processing operations (such as stirring, mixing, and filling) and storage stability of dairy products. By applying rheology, the production processes of dairy products can be optimized, enhancing production efficiency and product consistency. Dairy products like cream and whole milk function as emulsion systems. Thus, rheological analysis elucidates oil droplet dispersion, interfacial stability, and emulsifier functionality, which collectively govern resistance to stratification and the preservation of desirable texture during storage.[68] Furthermore, rheological characterization allows prediction of temperature- and time-dependent structural evolution in dairy products, including melting, phase separation, and texture deterioration during storage.[69,70]

Blending is a critical unit operation in dairy processing, as it directly influences flow behavior, phase distribution, and final textural uniformity. Rheological behavior plays a critical role in evaluating and optimizing this process. The incorporation of emulsifiers and other additives significantly influences the rheological characteristics of dairy products.[71] In cream making, effective blending of aqueous and fat phases determines emulsion stability, resistance to coalescence, and the development of a smooth and spreadable texture.

Numerous dairy products, such as yogurt and cheese, undergo the development of protein-based gel structures during fermentation, with their rheological responses directly indicative of gel strength, firmness, and other critical textural attributes. Throughout fermentation, the metabolic activity of microorganisms generates acidic byproducts that denature milk proteins, leading to gel formation.[72] Rheological properties, such as gel firmness, elasticity, and viscosity, provide valuable insights that assist in optimizing fermentation time, temperature, and microorganism activity, thereby enhancing gel formation and improving the textural qualities of dairy products. Rheology serves as a key tool in monitoring the coagulation and ripening processes of cheese, ensuring that its firmness and elasticity reach optimal levels. Rheological measurements are routinely employed to optimize fermentation time and temperature in yogurt production, enabling simultaneous control of viscosity, gel stability, and final textural quality.

Various dairy products, such as flavored yogurt and milk tea, frequently incorporate fruit particles, flavoring agents, or other suspended materials. Rheological analysis provides insights into how these particles disperse and settle within the liquid phase, facilitating uniform distribution and preventing sedimentation or phase separation. Furthermore, rheological models are applied to evaluate how particles of different sizes,

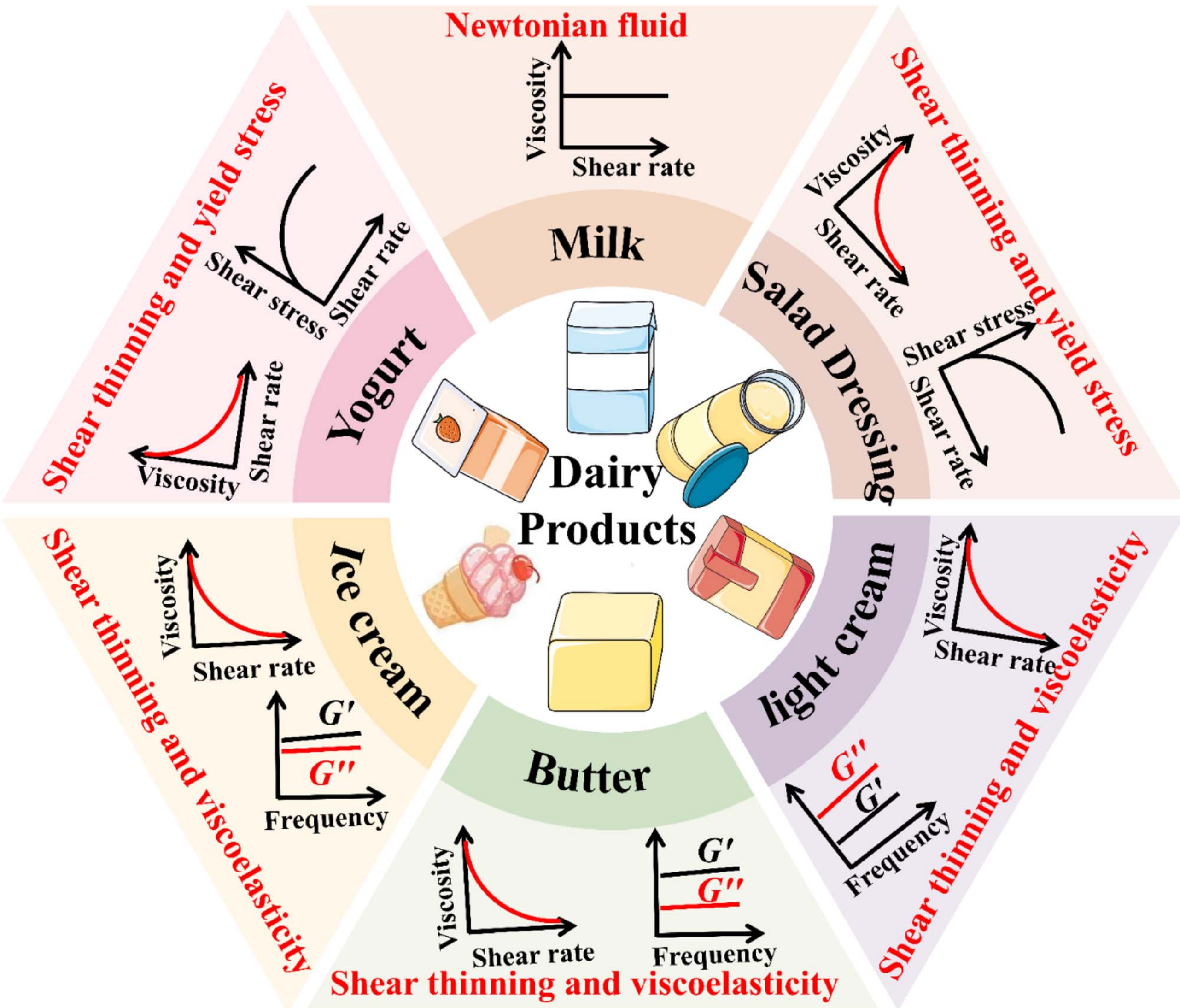

Fig. 2 Application of rheology in dairy products.

shapes, and concentrations affect flow resistance, suspension stability, and perceived texture of dairy products. This research guides the selection of appropriate mixing and handling techniques.

The rheological properties of dairy products are also crucial in packaging and transportation, as the rheological behavior—such as fluidity and consistency—of liquid or semi-solid dairy products dictates the speed and precision of filling during the packaging process.[73] The rheological properties of cream and yogurt are critical for ensuring uniformity and preventing leakage during packaging operations.[74] Viscosity, elastic modulus, and yield stress significantly influence the stability of dairy products during transportation, particularly under conditions of substantial temperature fluctuations. Overall, rheology serves as a predictive and control framework for managing structural integrity and texture retention of dairy products throughout packaging and transportation.

2.3.2 Drinks and soups. In drinks and soups, rheological properties are closely linked to texture perception and overall sensory quality, making rheological analysis an essential tool for formulation design and quality control. The viscosity of beverages, such as fruit juices, is directly associated with perceived smoothness and suspension stability, which together determine the uniformity and mouthfeel of the product.[75] Rheological testing facilitates the optimization of beverage formulations by adjusting sugar, thickener, and stabilizer levels to achieve the desired viscosity and rheological behavior. Similarly, rheological properties are paramount in determining the viscosity and smoothness of soups. Soup products with different visual and textural characteristics exhibit distinct rheological signatures. Thick soups are typically characterized by moderate viscosity, measurable yield stress, and pronounced shear-thinning behavior, which contribute to coating ability, prolonged oral residence, and a rich, creamy texture. In contrast, clear soups generally display low viscosity and negligible yield stress, enabling rapid flow, minimal oral coating, and a light, refreshing texture.[76] Furthermore, yield stress has been widely associated with the oral force required to initiate flow during swallowing, making it a critical parameter in the formulation of beverages and soups for populations with dysphagia or special swallowing requirements.[77]

Drinks and soups are typically multiphase systems, such as emulsions, suspensions, or weak gels, in which rheological properties play a decisive role in physical stability and texture retention during storage. Rheological analysis provides methods to assess and improve the stability of these intricate systems. Juices and vegetable protein drinks are prone to phase separation and layering. Rheological measurements have been widely used to optimize stabilizer systems, such as pectin and xanthan gum, in fruit juices and plant-based protein drinks, thereby improving viscosity control, particle suspension, and resistance to phase separation.[78] In thick and creamy soups, rheological analysis can control oil droplet size distribution and stability, preventing oil–water separation.[79]

Handling of drinks and soups involves mixing, pumping, and filling operations, which are closely related to flow and rheological behavior. Rheological analysis can optimize these processes. In practical processing, yield stress and shear-dependent viscosity are key parameters governing pumping, filling efficiency, and flow stability of thickened drinks and soups. In many cases, thickened soups and beverages exhibit a yield stress – a minimum stress threshold that must be exceeded before flow begins. Consequently, pumps and filling equipment must provide sufficient pressure to overcome this yield stress; otherwise, the fluid will remain essentially solid-like and resist flow. Rheological measurements can assist in adjusting processing temperatures or pumping forces.[76] Thickeners and some beverages may exhibit viscosity changes during high-temperature processes, such as sterilization or cooking. Rheological analysis enables the prediction of temperature-induced viscosity and texture changes during thermal processing, allowing timely adjustment of formulation and processing parameters.

Thickeners and stabilizers are essential constituents that substantially affect the rheological characteristics of beverages and broths. Rheological analysis serves as a critical tool for evaluating and optimizing the type and amount of these additives to meet specific product requirements. Rheological techniques are extensively employed to investigate the thickening and structuring effects of starch, pectin, and xanthan gum, enabling precise control of viscosity, yield stress, and textural attributes in broths and beverages.[78,80] Meanwhile, changes in yield stress caused by thickeners may affect the flow behavior and sensory properties of food. Evaluating the dissolution and dispersion of thickeners in beverages, along with optimizing their dosage, can improve sensory qualities without compromising rheological behavior.

Rheological analysis is critical in the development of functional beverages and certain broths, particularly in optimizing flavor, stability, and nutrient distribution. Functional beverages, such as high-protein and dietary fiber-enriched drinks, exhibit rheological characteristics that significantly impact consumer acceptance.[81] Rheological measurements are instrumental in balancing the challenges of viscosity, texture, and stability associated with high levels of protein, dietary fiber, or bioactive ingredients in functional beverages. In the context of concentrated and instant soups, rheological analysis is employed to optimize formulations, ensuring that appropriate rheological properties are maintained after mixing or cooking.[82]

2.3.3 Flour-based products. Dough is the foundational element in flour-based products, and its rheological and mechanical properties jointly govern processing behavior and the texture of the final products. Suitable elasticity and extensibility are essential not only for rolling and forming operations but also for determining the firmness, resilience, and bite of finished flour-based products. Rheological assessments are instrumental in characterizing gluten network development, which directly correlates with textural attributes such as hardness, cohesiveness, and chewiness in baked products.[83] The viscoelastic properties of dough dictate its behavior during various stages of processing, such as mixing and kneading. Through rheological studies, adjustments can be made to the protein content of flour or the addition of improvers to enhance processing performance. Time-dependent changes in dough rheology, such as softening or stiffening, are closely associated with variations in mechanical strength and textural stability of flour-based products.[84] By utilizing rheological analysis, these changes can be predicted and managed, thus enhancing the consistency of flour product production. For example, rheological characterization during baking provides insights into dough expansion, gas cell stabilization, and structure setting, which collectively determine crumb structure and textural uniformity,[85] and rheology can guide dough modification through key elastic and tensile properties.[86]

Fermentation is essential in the production of many flour-based products, including bread and steamed buns, by influencing both the rheological properties of the dough and the development of its solid texture post-baking or steaming. Its success is closely linked to the rheological properties of dough. During fermentation, it is crucial for the dough to retain carbon dioxide, which creates an airy structure.[87] Rheological examination is critical for assessing gluten network strength and elasticity, which determine gas retention during fermentation and ultimately control crumb softness and pore structure in the final product. It is imperative for the dough to maintain stable rheological properties throughout the fermentation process to prevent excessive coalescence or collapse of gas bubbles.[88] Rheological investigations are instrumental in the selection of suitable yeast strains and additives, thereby enhancing the outcomes of the fermentation process.

Rheological properties greatly influence the efficiency of these tasks. By utilizing rheological analysis, dough pliability and tensile strength can be improved to avoid issues such as cracking or shrinking during rolling. In noodle production, appropriate shear-thinning behavior and tensile strength are essential for sheet formation and cutting, while mechanical properties directly influence noodle firmness, elasticity, and chewiness after cooking.[89] Rheology is critical in improving flour-based product recipes, especially in adjusting water, protein, oil, and additive levels. Rheological evaluations are critical in assessing the performance of various flour types. The addition of thickeners (*e.g.*, carboxymethyl cellulose, xanthan gum) or emulsifiers (*e.g.*, monoglycerides) modifies dough rheology and mechanical strength, leading to improved softness, cohesiveness, and textural stability of flour-based products.[90,91]

Rheological characteristics directly determine the mechanical texture of flour-based goods, including firmness, elasticity, and crispness, which are key quality attributes for consumer acceptance. Rheological behavior can enhance the gluten network's strength and extensibility, achieving a more voluminous bread framework. Furthermore, rheological properties contribute to optimizing noodle firmness and smoothness, thereby enhancing the consumer's dining experience.[92] By analyzing dough deformation and fracture behavior at low moisture content, rheological approaches contribute to the design of crispy and brittle flour-based products such as crackers and biscuits.

During baking, flour-based goods experience complex physical and chemical changes, and rheological analysis provides critical insights. Rheological analysis aids in examining starch gelatinization and protein denaturation during heating, which governs structure setting and the mechanical texture of baked products.[93] By studying bubble behavior in dough using rheological analysis, baking temperature and duration can be optimized for an even pore structure in baked goods.

Rheology plays a key role in the development of quick-frozen dough products, including quick-frozen dumplings and buns. During freezing and thawing, changes in dough rheology and mechanical strength may lead to texture deterioration and structural failures, such as cracking or loss of elasticity, in flour-based products. Rheological testing serves as a valuable tool for screening antifreeze agents and enhancing the stability of frozen products.[94] During freezing, water migration exerts a significant influence on the dough's structure. Rheological analysis facilitates the optimization of moisture content and freezing conditions, thereby contributing to the preservation of the product's texture.

2.3.4 Gel-like foods. The study and application of rheology in gel-like foods are essential, as these semi-solid systems exhibit distinct mechanical and textural characteristics that are directly governed by their rheological properties. By analyzing these properties, the production process can be refined, product quality can be improved, and diverse market needs can be met.

The texture of gel-like foods, such as jelly, pudding, cheese, and yogurt, is primarily determined by their rheological and mechanical characteristics. Rheological assessments commonly involve measuring the storage modulus (G') and loss modulus (G''), which are closely associated with gel elasticity, firmness, fracture resistance, and overall structural integrity. These rheological parameters enable targeted formulation adjustments, such as modifying polymer concentration or crosslinking density, to tailor gel firmness, cohesiveness, and deformation behavior. Ibraheem *et al.* applied a machine learning model to predict the impact of aloe vera gel addition on gel rheology, achieving a high prediction accuracy.[95] Depending on the specifications of the target product, the gel's firmness can be tailored by utilizing rheological analysis. In pudding production, gel elasticity and yielding behavior are carefully controlled to obtain a soft, easily deformable texture that disintegrates smoothly during oral processing.

Gel formation is a dynamic process governed by temperature, time, pH, and additive concentration, all of which influence network development and final mechanical texture. Rheology is an essential analytical tool for monitoring and optimizing the dynamic process of polymer formation. In protein-based gels, rheological monitoring of G' evolution during heating and cooling provides insight into network formation, structure setting, and the resulting firmness and brittleness of the gel.[96,97] During the gelation of yogurt, rheological analysis is employed to monitor network development under varying acidity, enabling control over gel uniformity, firmness, and resistance to syneresis.[98] In cheesemaking, rheological studies examine how enzyme-induced gelation affects network strength and fracture behavior, which are critical for curd cutting and the final texture of the cheese.[99]

Rheology is critical for assessing the mechanical stability and shelf life of gel-like food products. These items, which are often subjected to external forces such as shaking or shear stress during transportation and storage, require careful handling. Many gel-like foods exhibit a measurable yield stress, which serves as a mechanical threshold for deformation and governs resistance to collapse, flow, or fracture during handling and transportation. Changes in yield stress and viscoelastic moduli during storage indicate structural weakening and increased risk of syneresis or collapse, allowing rheological testing to serve as a predictive tool for texture degradation. Rheology is often used to monitor the aging process of food emulsions, evaluate structural changes in products during prolonged storage, and detect water separation. By fine-tuning formulation and processing parameters based on rheological indicators, both the structural stability and textural quality of gel-like foods can be effectively maintained over shelf life.

2.3.5 Sugar confectionery. Sugar confectionery encompasses a diverse category of products such as hard-boiled candies, caramels, toffees, gummies, and jelly candies, whose quality is primarily defined by mechanical texture rather than flow behavior. These products exhibit distinct rheological–textural signatures governed by carbohydrate concentration, crystallinity, water activity, and hydrocolloid composition. Unlike liquid foods, sugar confectionery systems are often characterized by glassy or rubbery states, where small changes in formulation or processing can result in pronounced differences in fracture behavior and oral perception.

Hard candy systems are dominated by amorphous sugar glasses, and their mechanical behavior, including brittleness, stick-slip fracture, and cracking, mainly depends on their glass transition temperature (T_g) and degree of supersaturation. Above the T_g, sugar matrices exhibit rubbery viscoelastic deformation associated with deformable or slightly chewy textures, whereas below the T_g they behave as rigid brittle solids that undergo catastrophic fracture upon biting, producing sharp and abrupt textural sensations.[100] Rheological characterization around T_g therefore provides a critical framework for controlling hardness, fracture energy, and shelf stability of hard candies.

For soft sugar confectionery, such as gummies, jellies, and caramels, texture is governed by elastic or viscoelastic gel networks formed by gelatin, starch, or pectin. In these systems, rheological parameters such as storage modulus, yield stress, and relaxation behavior are directly associated with chewiness, cohesiveness, and recovery after deformation. Processing conditions—including cooking temperature, acidification, evaporation rate, cooling profile, and mechanical agitation—strongly influence sucrose crystallization, hydrocolloid hydration, and network formation, thereby determining final texture and structural uniformity.[101] Consequently, rheology provides a quantitative tool for linking processing to mechanical texture and consumer perception in sugar confectionery.

2.3.6 Extruded foods. Extruded foods, including puffed snacks, extruded cereals, protein-based meat analogs, high-moisture extrudates, and starch–protein composite structures, depend critically on the rheology of the melt undergoing high shear, pressure, and temperature within the extruder barrel, which governs structure formation and final texture. During extrusion, materials are subjected to extreme shear, pressure, and temperature, transforming them into multiphase viscoelastic melts whose rheological properties determine flow behavior within the extruder and structural evolution at the die.

Starch plays a central role in most extrudates. During extrusion, starch granules gelatinize and undergo fragmentation, water uptake, melting, and molecular entanglement. The resulting thermoplastic starch melt behaves as a nonlinear viscoelastic fluid, and its relaxation time spectrum and extensional viscosity largely dictate bubble growth, expansion ratio, cell wall thickness, and crispness.[102] Protein-rich extrudates, such as texturized plant proteins or high-moisture extruded meat analogs, rely on protein denaturation, alignment, disulfide crosslinking, and fibril formation governed by melt rheology under shear and elongation, leading to anisotropic, meat-like textures.[103]

The interplay between rheology and processing parameters controls structure development. Higher melt viscosity and elasticity typically lead to greater expansion and more porous structures in low-moisture puffed snacks, but in high-moisture meat analogs, excessive viscosity may impede fiber alignment and reduce the formation of anisotropic, meat-like layered structures.

2.3.7 Reformed flesh or surimi foods. Reformed flesh foods, including surimi gels, comminuted meats, sausages, emulsified meats, and reconstructed or formed meat products, rely heavily on the rheology of myofibrillar protein networks developed during mixing, salting, comminution, heating, and emulsification. In these systems, texture is primarily determined by the viscoelastic and viscoelastic behavior of myofibrillar protein matrices rather than simple flow properties.

Myosin extraction and solubilization under salt and mechanical action produce a sticky, viscoelastic protein matrix whose G', yield stress, and viscosity define its ability to bind water, fat droplets, and meat fragments. During thermal gelation, myofibrillar proteins unfold, aggregate, and form three-dimensional networks, which determine gel strength, water-holding capacity, cohesiveness, elasticity, and slicing stability.[104]

In surimi systems, the rheological response during setting and gelation is highly sensitive to proteolytic activity, protein concentration, cryoprotectant composition, and ionic strength. Oscillatory rheology provides detailed insights into the gelation kinetics, network formation, and degradation. More advanced applications, such as hybrid meat–polysaccharide emulsion gels or surimi-based 3D-printed structures, rely on tailored viscoelastic behavior and thixotropy to ensure both printability and final structural integrity.[105]

2.3.8 Novel foods. As the food industry evolves rapidly, the variety of novel food products, including plant-based foods, solid fat substitutes, dysphagia diet, functional foods, and 3D-printed foods, continues to expand. Rheology plays a critical role in characterizing and designing the mechanical strength, deformation behavior, and solid-like or semi-solid structures of novel foods, which directly determine their texture, stability, and processability.

In the development of plant-based products, such as plant-based meats, plant milks, and vegetable cheeses, achieving a texture and taste comparable to traditional counterparts is critical for consumer acceptance. Rheology is employed to regulate the viscoelasticity, yield behavior, and extensional deformation of plant proteins under high shear conditions, thereby enabling the formation of fibrous, layered structures with meat-like firmness, chewiness, and tensile resistance.[106] By adjusting G', nonlinear viscoelastic response, and strain-dependent deformation behavior, plant proteins such as soy or pea can be engineered to reproduce the chewiness and elasticity characteristic of meat products. Indeed, the production of plant-based milk and vegetable cheese relies on effective blending and suspension properties. Rheological evaluation of viscosity, yield stress, and low-frequency elastic response assists in optimizing emulsifier systems, thereby controlling the thickness, spreadability, and suspension stability of plant-based milks and vegetable cheeses.[107] High-moisture extrusion technology is extensively utilized in the manufacture of plant-based meat products. Rheology is instrumental in examining the viscoelastic transformations of proteins under high-temperature and high-pressure conditions, thereby informing equipment design and process optimization.

In response to the growing demand for healthier food options and concerns regarding cardiovascular diseases, the food industry is increasingly focused on reducing the use of saturated and trans fats. The development of solid fat substitutes relies heavily on rheology to quantify and tailor solid-like mechanical strength, plastic deformation, and spreadability, which collectively define fat-like texture and processing performance. Liquid vegetable oils are transformed into solid fat-like forms through structuring processes, with rheology employed to evaluate and optimize their performance. These oils are converted into semi-solid structures using structuring agents such as waxes.[108] Rheological analysis, particularly storage modulus (G'), loss modulus (G''), and yield stress, is utilized to characterize gel firmness, structural stability, and resistance to deformation under spreading or mastication. High internal phase Pickering emulsions (internal phase ≥ 74%), prepared with soft particle emulsifiers such as proteins and starches, are designed to mimic the texture of traditional solid fats.[109] Rheological testing evaluates viscoelasticity, yield behavior, and shear-thinning characteristics to achieve fat-like firmness, controlled flow, and desirable mouth-coating behavior. The development of substitutes with health benefits necessitates a reduction in saturated fat content.

The rheological properties of food are crucial in the formulation of dysphagia diets. The International Dysphagia Diet Standardization Initiative (IDDSI), established in 2012, aims to provide globally standardized terminology and definitions for foods and liquids suitable for individuals with dysphagia, as illustrated in Fig. 3.[110] According to the IDDSI framework, foods and beverages are categorized based on their rheological responses to deformation, including viscosity, yield stress, and structural integrity during oral processing. Specifically, foods are categorized into groups into categories such as easy-to-chew items and those that have been modified through processing techniques like softening, mincing, pureeing, or liquefaction.[3] Liquid foods are often thickened with hydrocolloids to achieve controlled viscosity, yield stress, and bolus cohesiveness, thereby ensuring safe swallowing and structural stability during oral transport. The IDDSI framework delineates beverage textures into five distinct categories: extremely thick, moderately thick, mildly thick, slightly thick, and thick. In consideration of the dietary practices of the Chinese population, foods are further divided into two primary categories: liquid and solid, with a total of six levels defined according to their properties and forms in Fig. 3.[111] In the context of the swallowing process, shear and tensile deformations are critical. During the oral phase, the food bolus experiences shear deformation within the constrained space between the tongue and the palate in the oral cavity. Consequently, rheological parameters such as low-shear viscosity, yield stress, and deformation resistance can be strategically designed to control bolus cohesiveness, oral stability, and swallowing safety.

Functional foods often incorporate ingredients such as probiotics, dietary fiber, and antioxidants to address specific health requirements. Rheology plays a crucial role in regulating matrix firmness, elastic strength, and deformation behavior, which govern texture, physical stability, and the protection of bioactive components. Dietary fiber significantly influences the rheological properties of food, including viscosity and elasticity. Rheological approaches adjust fiber level and type to control viscosity, elastic modulus, and network strength, thereby balancing health functionality with acceptable firmness and mouthfeel.[73] In yogurt, the stability of probiotics is closely linked to the rheological traits of the carrier matrix.[112] Rheological measurements enhance the viscoelasticity and gel strength of the carrier, maintaining probiotic viability during processing and storage. The release rate of active compounds, such as vitamins and antioxidants, in functional foods is impacted by the rheological properties of the delivery system. Rheological studies assist in designing slow-release or

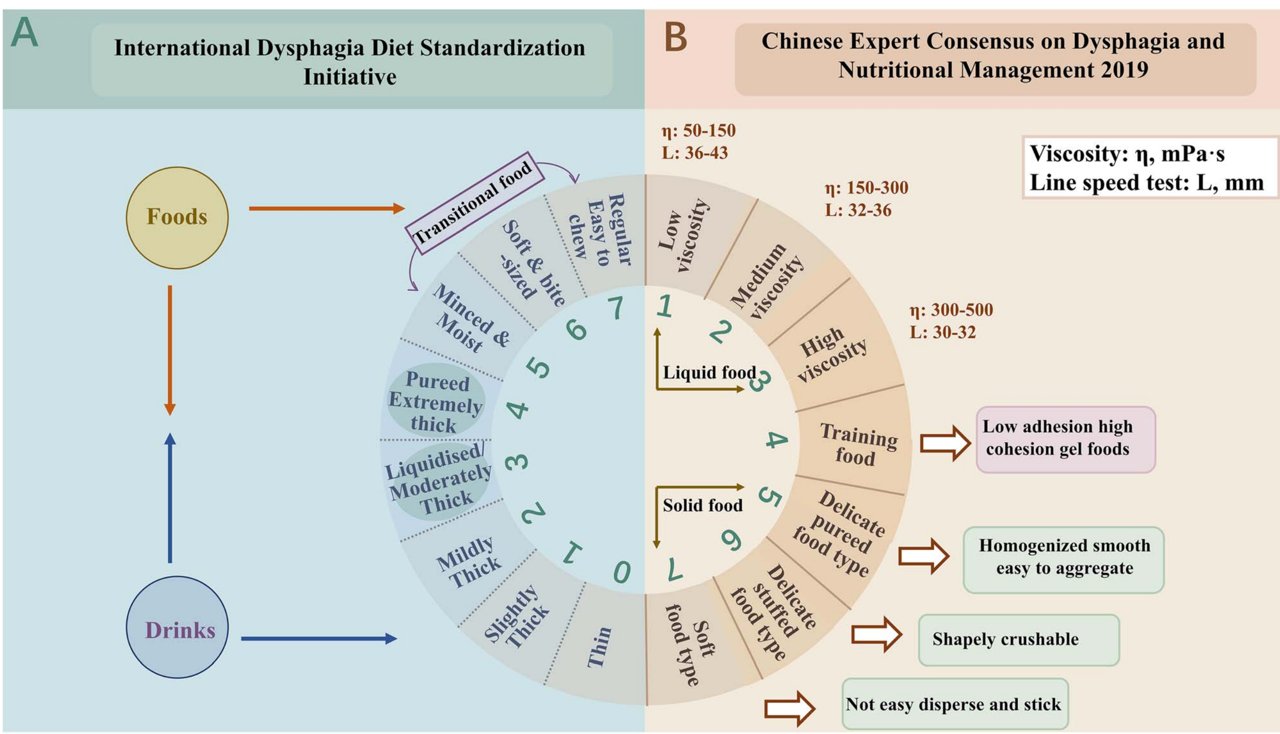

Fig. 3 Description of international (A) and Chinese (B) food and beverage products with different texture characteristics. This figure is reproduced from ref. 3 with permission from Elsevier,[3] copyright 2025.

controlled-release systems, which may involve floating particles or gel beads in functional beverages.[113]

The advent of 3D-printed food represents a pioneering advancement in food innovation, with its processing heavily dependent on the rheological properties of the food materials. Rheology is instrumental in quantifying yield stress, viscoelastic flow, and post-extrusion elastic recovery, which collectively determine printability, shape retention, and structural firmness of printed foods. The layered architecture of printed food necessitates a specific degree of viscoelasticity to prevent structural collapse. By tuning G', G'', and their ratio, the mechanical stability, layer adhesion, and final textural firmness of printed structures can be precisely controlled.[88] Moreover, rheological analysis enables the development of printing materials with diverse textures and nutritional profiles.

3. ML in rheology

Rheology, the scientific study of the flow and deformation behavior of materials under varying conditions, finds extensive applications within the domain of food science, particularly in optimizing food texture, taste, stability, and processing parameters. However, the inherent complexity of food materials and the nonlinear characteristics of their rheological properties present significant challenges to traditional rheological models, which often struggle to accurately predict and elucidate rheological behavior in food systems. In this context, the integration of ML technology into food rheology research provides innovative solutions to these challenges. By processing vast datasets and discerning intricate nonlinear relationships, ML enhances model performance, augments predictive capabilities, and optimizes rheological properties. Application examples of ML in food rheology are summarized in Table 2. The process of applying ML in food rheology is shown in Fig. 4a.

3.1 Fundamental processes in ML

ML employs various methodologies, encompassing supervised, unsupervised, and reinforcement learning, to process data and address diverse tasks. Supervised ML, predominantly used for classification and regression, is widely applied to model

Table 2 Application examples of ML in food rheology

Food system	Key objectives	Main rheological parameters	Main ML model	Accuracy	References
Starch gels	Identifying whether a food is suitable for the elderly	Universal design food test, puncture test	Quadratic polynomial	98%	114
Starch paste	Predicting melt–stretch properties	Melt–stretch properties, viscosity, viscoelasticity	Binary classification	93.3%	4
Protein dispersion system	Predicting the viscosity	Viscosity	Decision tree regressor, Gaussian process regressor	R^2 > 99%	115
Protein–polysaccharide solution	Predicting rheological parameters of food biopolymer mixtures	Small, medium, and large amplitude oscillatory shearing	Random forest	$R^2 = 0.94$	116
Bouillon	Decode relationships between non-Newtonian and their perceived texture	Viscosity	Neural network	Accurately predict	117
Yogurt	Predicting the sensory and texture	Large-amplitude oscillatory shearing	Random forest regression	RMSE < 6	118
Yogurt	Predicting the texture of yogurt	Thixotropy, viscosity	Artificial neural network	R^2 > 95%	119
Mayonnaise	Predicting the viscosity	Viscosity, yield stress	Extreme gradient boosting, gradient boosting regression, random forest	$R^2 = 0.996$	120
Pectin	Predicting ink properties during 3D printing	Viscosity, viscoelasticity	Extreme gradient, extra trees, extreme gradient, decision tree, random forest	$R^2 = 0.944$	6
Pectin gummies	Predicting ink properties during 3D printing	Viscosity, viscoelasticity	Decision tree	87.5%	121
Methylcellulose	Predicting the viscosity	Viscosity	Random forest, multilayer perceptron	$R^2 = 0.996$	122
Apple puree	Predicting the viscosity	Viscosity	Generalized linear, gradient boosting	$R^2 = 0.78$	123
Rice flour	Oil uptake prediction of rice flour in a batter-coated fried system	Viscosity	Generalized linear, gradient boosting	$R^2 = 0.78$	124
Meat	Predicting textural properties by simulating chewing	Chewiness	Extreme gradient boosting	97%	125
Meat	Predict the textural properties	Hardness, chewiness	Ridge, extreme gradient boosting, multilayer perceptron	RMSE < 15	126
Pork snacks	Predicting the texture of puffed products	Hardness	Artificial neural network	$R^2 = 90\%$	127

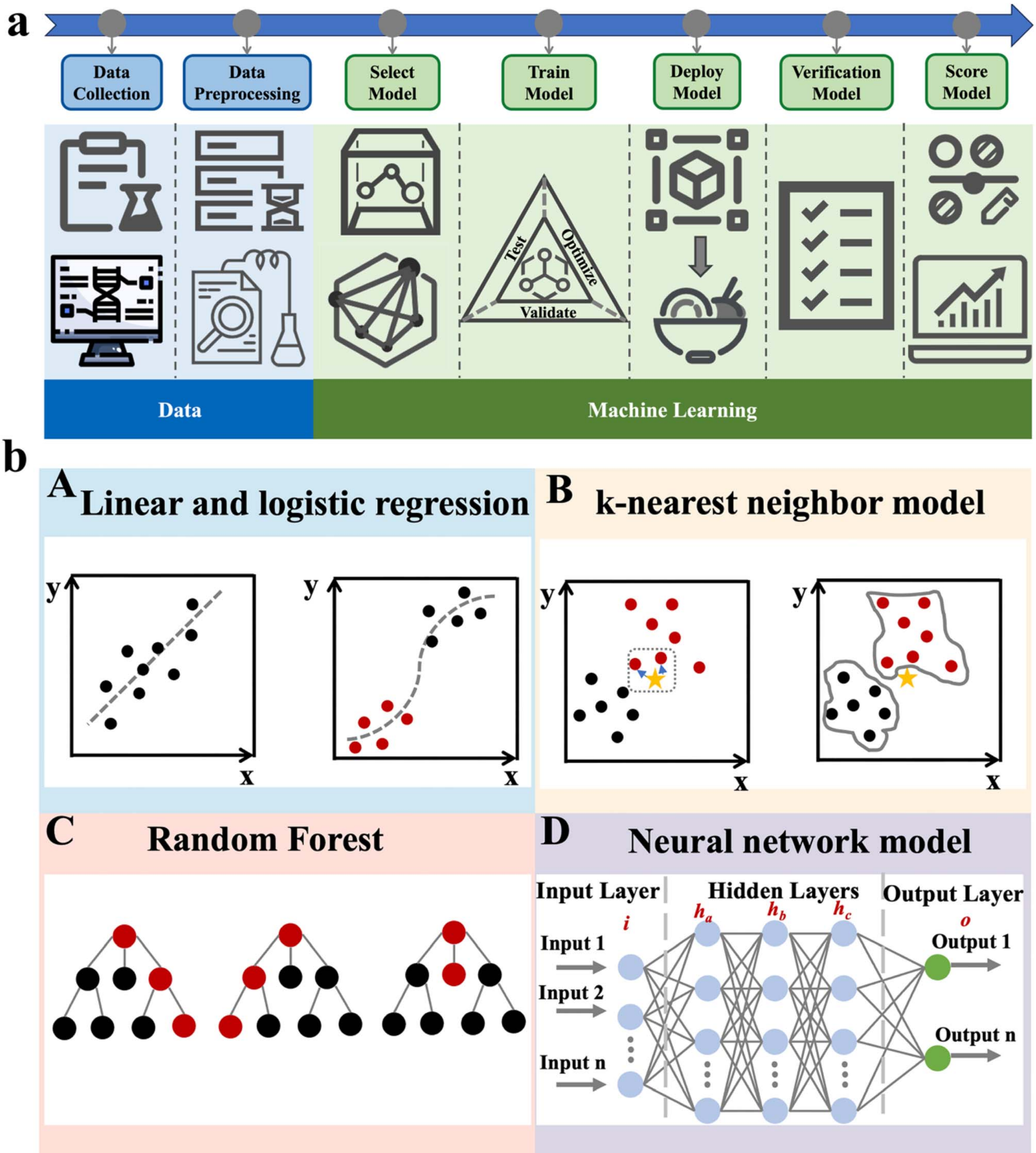

Fig. 4 (a) Schematic diagram of ML application in food rheology; (b) schematic diagram of common ML models in food rheology.

relationships between formulation or processing variables and rheological responses such as viscosity, elastic modulus, yield stress, and firmness-related mechanical behavior. Unsupervised ML is employed to uncover latent structures within high-dimensional rheological datasets, enabling the identification of underlying structural similarities associated with texture-related mechanical responses. Reinforcement learning is particularly effective in optimizing dynamic processing conditions, such as mixing, heating, or extrusion, where rheological and textural targets must be continuously adjusted in real time. Collectively, these ML methodologies enhance the efficiency and precision of analyzing, predicting, and controlling rheological and texture-related mechanical properties of foods.

The application of ML in food rheology commonly encompasses four fundamental tasks: dimensionality reduction, classification, regression, and clustering.[128] Dimensionality reduction aims to condense complex rheological datasets by removing redundant variables while retaining key descriptors of flow behavior, viscoelasticity, and mechanical strength relevant to texture. Classification tasks enable the categorization of food samples according to rheological signatures, such as soft *versus* firm gels, brittle *versus* elastic solids, or low- *versus* high-yield-stress systems. Regression tasks are used to predict continuous changes in rheological and texture-related parameters, including viscosity, elastic modulus, yield stress, and fracture-related responses, as functions of formulation or processing conditions. Clustering tasks involve grouping samples that exhibit similar rheological and mechanical behavior, thereby aiding in the identification of food categories with comparable texture and deformation characteristics. In food rheology, these tasks collectively support model development, formulation optimization, and process control by linking measurable mechanical responses to product texture and performance.

In food rheology, ML is typically implemented through a systematic workflow aimed at predicting and optimizing flow, deformation, and texture-related mechanical properties *via* data-driven modeling. Data collection and preprocessing involve acquiring rheological and mechanical data, such as viscosity, elastic modulus, yield stress, firmness, and deformation resistance, followed by cleaning, normalization, and noise reduction. Feature engineering focuses on extracting informative variables, including shear rate, strain, temperature, time, and derived rheological descriptors that capture texture-relevant mechanical behavior. Appropriate ML algorithms, including regression, classification, clustering, or deep learning models, are then selected to establish quantitative relationships between processing variables and rheological responses. Model evaluation is performed using independent test datasets to assess prediction accuracy and generalization, ensuring reliable estimation of rheological and texture-related properties across different food systems.

3.2 ML models used in food rheology

Traditional rheological models typically rely on explicit mathematical formulations and simplifying assumptions, which may inadequately capture complex rheological responses associated with texture-related mechanical behavior in real food systems. In contrast, ML offers a data-driven approach to rheological modeling, enabling the construction of predictive models through the identification of patterns and regularities within historical datasets. As a result, ML-based rheological models are increasingly used to jointly predict flow behavior and texture-related mechanical responses across liquid, semi-solid, and solid foods.

3.2.1 Regression model. In the domain of ML, regression techniques, encompassing linear regression, support vector regression (SVR), decision tree regression, random forest regression, and gradient boosting regression, are extensively employed to predict rheological behavior (Fig. 4b).[129] Within food rheology, these regression models are primarily used to establish quantitative relationships between formulation or processing variables and rheological descriptors, including viscosity, elastic modulus, yield stress, and firmness-related mechanical responses.

The linear regression model, a fundamental ML algorithm, is employed to investigate the linear relationships between two or more variables.[130] Specifically, in food rheology, linear regression models are frequently utilized to quantitatively analyze the relationships between rheological properties (*e.g.*, viscosity, elastic modulus, shear strength, and firmness) and their influencing factors (*e.g.*, ingredient ratios, processing parameters, and temperature).[131]

The linear regression model is favored for its simplicity, computational efficiency, and high interpretability, offering straightforward implementation and effective visualization capabilities. However, this model is limited to capturing linear relationships between variables and tends to perform inadequately when addressing complex nonlinear problems. Furthermore, the presence of strong multicollinearity among input variables can result in unstable and unreliable coefficient estimates.

The *k*-nearest neighbors (*k*NN) algorithm is a non-parametric ML method widely employed for both classification and regression tasks.[132] In the domain of food rheology, *k*NN is employed to predict and classify samples based on similarities in their rheological and texture-related mechanical profiles, such as viscosity curves, viscoelastic spectra, and compression-derived firmness.[131] When presented with a new data point, the algorithm determines its distance from all points within the training dataset and subsequently selects the *k* nearest neighbors to establish the output. Classification outcomes are derived from the majority class among the *k* neighbors, while regression predictions are made using either the average or a weighted average of the output values of these neighbors.[133] Notably, *k*NN does not require assumptions about the data distribution, rendering it well-suited for modeling intricate rheological data. Moreover, the *k*NN model is adept at in handling multidimensional data, thereby enhancing its applicability to classification and regression tasks. However, the method incurs high computational cost, is sensitive to experimental noise, and strongly depends on feature selection, particularly when texture-related mechanical data are included.

Decision trees, the basic unit of random forest, are a class of ML models applicable to both classification and regression tasks.[132] In the field of food rheology, decision tree models are extensively employed to analyze and predict complex rheological properties due to their inherent interpretability and computational efficiency.[134,135] These models recursively partition data using splitting criteria such as the Gini index or information gain, with rheological and texture-related mechanical parameters serving as decision variables. The partitioning process continues until a predetermined stopping condition is satisfied, such as reaching a minimal sample size at a node or a specified tree depth limit. Based on the input of food rheological properties, branches corresponding to feature values are selected along the tree path, ultimately leading to the output category at the leaf node. For predicting continuous numerical properties, such as viscosity and elastic modulus, the output at the leaf node is typically the average or weighted value of the target variable. Decision trees have emerged as a useful analytical tool in food rheology, particularly for linking formulation variables to rheological and texture-related mechanical outcomes in solid and semi-solid foods. When integrated with sophisticated pruning techniques and ensemble methods, such as random forests and gradient-boosting trees, the potential applications of decision trees within the food industry are significantly enhanced.

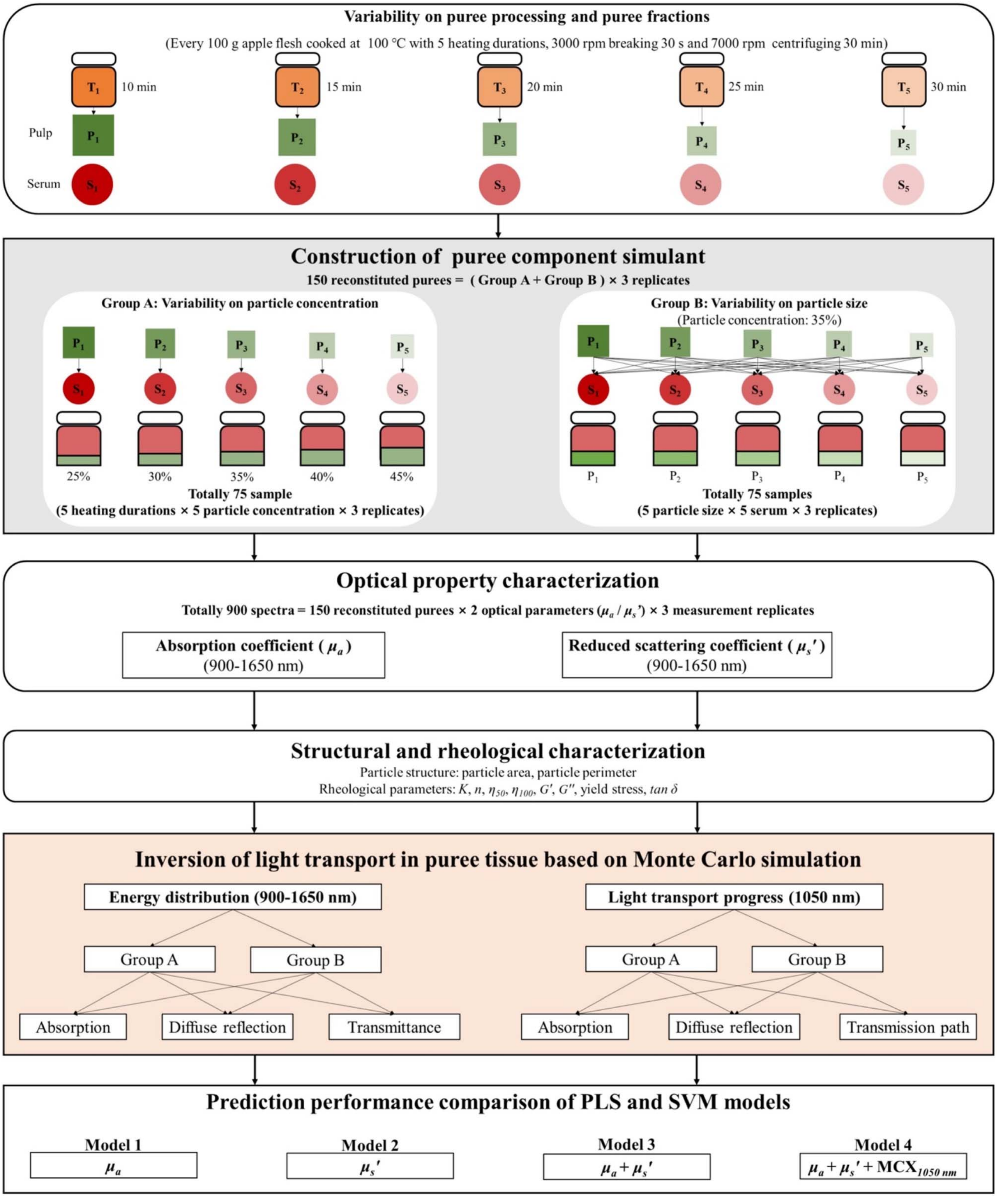

Fig. 5 Prediction of rheology by SVM model. This figure is reproduced from ref. 100 with permission from Elsevier,[100] copyright 2022.

The Support Vector Machine (SVM) is a robust supervised learning algorithm commonly utilized in both classification and regression tasks.[132] In food rheology, SVM leverages rheological features, including viscosity, elastic modulus, yield stress, and deformation-related mechanical indicators, for data modeling and prediction. This support facilitates the improvement of processing techniques, recipe design, and product quality management.[136–138] SVM identifies an optimal hyperplane within the feature space to effectively separate data points, thereby maximizing the margin between classes.[139] Yang *et al.*[140] effectively evaluated the apparent viscosity, viscoelasticity, and elastic modulus of fruit puree using an SVM model, as depicted in Fig. 5. For non-linearly separable datasets, SVM employs kernel functions to map low-dimensional features into a higher-dimensional space, enabling the identification of linear hyperplanes in this transformed space for effective data separation. SVM classifies food rheological data by applying linear or non-linear kernel functions, including the Gaussian kernel and radial basis function kernel. The regression variant of SVM (SVR) is commonly used to predict continuous rheological and mechanical variables, such as viscosity, yield stress, and firmness-related responses, in food systems. SVMs offer a robust approach for classifying rheological behavior, predicting processing parameters, and examining storage stability in food rheology. Their strong nonlinear modeling capability and generalization performance make them particularly suitable for complex rheological datasets involving texture-critical foods, such as gels, doughs, and restructured solids. While challenges related to handling large datasets and model interpretability exist, the potential of SVMs within the food industry is expected to grow through parameter optimization and methodological advancements.

3.2.2 Neural network model. Neural networks, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are increasingly utilized in food rheology within the fields of ML and deep learning in Fig. 4b. These models excel at handling complex, non-linear, and time-series data, playing a key role in predicting and optimizing food rheological properties.

CNNs excel at extracting local features through convolutional layers and utilize pooling layers and fully connected layers for feature aggregation.[130] In food rheology, CNNs are effective in extracting microstructural and surface features from microscopic or texture images that are closely linked to rheological and mechanical responses. This involves examining the structural characteristics of substances such as dough, gels, and dairy products. These extracted features are subsequently used to predict rheological parameters, such as viscosity, elastic modulus, firmness, and resistance to deformation. By evaluating real-time image data, CNNs assist in detecting quality issues, such as layering, bubble distribution, or structural heterogeneity, and linking these features with rheological and texture-related indicators to enhance production processes.[141] CNNs' ability in efficient feature extraction and spatial relationship modeling makes them exceptional in image processing and modeling complex relationships in food rheology, boosting research efficiency and predictive accuracy.[138]

RNNs are commonly utilized in food rheology for handling and modeling rheological data characterized by time-series dependencies.[142] Rheology examines material flow and deformation behavior under time-dependent conditions, where texture-related mechanical properties evolve with shear history, temperature, and processing time. RNNs are well-suited for handling time-series data because they can effectively capture long-term dependencies and dynamic changes.[143] In food rheology, especially during prolonged storage or processing, the rheological properties of materials exhibit temporal fluctuations. Therefore, RNNs are effective tools for predicting the temporal evolution of rheological responses during processing and storage.

Moreover, Generative Adversarial Networks (GANs) have been utilized in food rheology, particularly for data augmentation and sample generation. GANs can generate synthetic rheological and mechanical datasets, including viscosity, elastic modulus, yield stress, and firmness-related responses across different temperatures and shear conditions. This capability contributes to expanding the rheological dataset and enhancing the model's training efficiency, especially when dealing with limited sample sizes. Moreover, GANs assist in improving the quality of food processing, such as fine-tuning gel formation in ice cream production or during fermentation. By generating synthetic rheological datasets, GANs provide more diverse and representative samples, supporting the optimization of texture, mechanical performance, and stability of food products.[144]

In summary, ML provides a practical and efficient new approach to rheological research. Traditional rheological models often depend on intricate mathematical formulas, requiring extensive experimental data and numerous assumptions. In contrast, ML employs a data-driven approach to autonomously discern complex patterns among raw material ratios, processing conditions, and rheological parameters using historical data. This approach markedly enhances the precision and efficiency of predicting rheological and texture-related properties, such as viscosity, elastic modulus, and firmness. Modern regression algorithms and neural network models can comprehensively consider multiple factors such as formulation composition, processing temperature, and shear rate, achieving accurate modeling of the flow properties of food materials and reducing the burden of manually deriving complex equations. For situations with limited data samples, methods such as GANs can enhance the dataset by synthesizing samples, thereby further improving the model's generalization ability. Overall, the application of ML in food rheology has emerged as a potent tool, facilitating the amalgamation of multi-source information, optimize production processes, and formulation design, and improve quality control, thus driving the food industry towards greater intelligence and efficiency.

4. Application of rheology combined with ML in food

4.1 Formulation optimization and food design

ML technologies have demonstrated significant potential in optimizing and developing food formulations, offering a transformative tool for the contemporary food industry. By analyzing the intricate non-linear interactions between food components and rheological properties, including viscosity, viscoelasticity, yield stress, and texture-related mechanical attributes, ML can identify critical factors and generate highly accurate predictive models. Recent advances have demonstrated that ML models can map rheological measurements directly to texture perception, such as thickness or mouthfeel, even with limited datasets through sensory-biased autoencoders.[145] These models enable practitioners to rapidly evaluate the impact of various components on rheological behavior, such as flowability, mechanical strength, and stability, thereby facilitating the development of optimal formulation recommendations.

The integration of ML with fine-tuning approaches, such as genetic algorithms and particle swarm optimization, enables the prediction and control of complex rheological responses, including those governing food texture and mechanical strength. In the food sector, accurately adjusting ingredient proportions is crucial for achieving specific rheological requirements. Bonilla *et al.*[146] demonstrated this by optimizing the formulation of egg white foams using basic meringue components. They systematically modified sugar levels and acidity conditions to enhance rheological responses associated with foam texture, including apparent viscosity and elastic dominance, resulting in a firmer and more stable structure. By analyzing rheological data alongside formulation factors, ML algorithms can effectively recommend the optimal ingredient proportions for desired rheological characteristics, thereby enhancing product quality and consistency.

Crafting food formulations often necessitates the simultaneous optimization of multiple rheological objectives, including flow behavior and texture-related mechanical performance. ML, in conjunction with multi-objective optimization methods, can effectively address these complex requirements by identifying optimal solutions through active modeling. Jamshidvand *et al.*[147] used ML to optimize a high-protein tomato soup for older adults by blending milk and pea proteins. The ML models predicted key rheological properties governing soup texture, including viscosity and stability-related viscoelastic behavior, and identified a formulation with doubled leucine content and a lower CO_2 footprint. This demonstrates ML's power to balance multiple targets (nutrition, sustainability, texture) when adjusting ingredients. Similarly, Ren *et al.*[148] developed a hybrid ML system combining electronic taste/olfactory sensors and algorithms to predict optimal formulas and process parameters for vegetable–fruit juice beverages. Their DNN model achieved $R^2 = 0.88$ when predicting both ingredient ratios and processing conditions from sensor data. ML approaches have been developed to predict textural properties of plant-based meat analogs, identifying key compositional factors such as carbohydrate and moisture content that drive firmness and chewiness outcomes.[149] Thus, by learning from lab or sensor data, ML can rapidly suggest new formulations that meet target rheological and sensory profiles. Many other examples show ML speeding up formulation trials. For instance, ML-optimized mixture designs have been used to improve rheological performance governing gel texture, baked goods, and emulsions by predicting how each component affects firmness, springiness, and structural stability.[150] In each case, the algorithms analyze past experimental data to model non-linear ingredient interactions, then recommend ingredient levels that simultaneously meet multiple objectives. These active-modeling approaches can incorporate genetic algorithms or particle-swarm optimization to fine-tune trade-offs. Overall, data-driven models enable formulators to cut trial-and-error iterations: given a desired texture or stability, the ML model immediately estimates the needed proportions and processing steps to achieve it.

Interestingly, ML can model sensory evaluation data to assess the impact of formulation components on sensory attributes, such as flavor and smoothness. Ding *et al.*[151] demonstrated that image processing combined with the SVM model could classify the smoothness of milk powder, thus predicting the flowability and handling properties of milk. This modeling approach enables the prediction of consumer liking for different formulations, providing valuable insights to enhance product development and market positioning strategies. Predicting oiliness sensations or analyzing textural attributes facilitates the creation of products that effectively satisfy market demands.

In health-focused foods, ML helps in crafting tailored formulations by regulating rheological properties that determine texture and ease of chewing, enabling the development of easy-to-chew products for specific demographics such as seniors. Furthermore, when integrated with sensors and real-time rheological data streams, ML algorithms can actively modify formulations to maintain product uniformity and quality throughout the production process.

4.2 Prediction and analysis of rheological behavior

A significant application of ML in food rheology is the prediction of rheological behavior, which includes flow, deformation, and structure-related attributes that are critical in determining food texture and processability. Through effective data analysis and modeling, ML enhances research efficiency and expands the range of potential applications. Characterizing food materials that exhibit pseudoplastic, dilatant, or Newtonian behavior, along with their associated textural properties, necessitates intricate and time-consuming experimental protocols. However, ML offers a promising alternative by leveraging existing datasets to rapidly predict the rheological characteristics of food under different situations, lowering experimental expenses and speeding up research and development.

ML approaches are highly effective in examining how food systems behave. These systems can predict variations in rheological properties, including viscosity, yield stress, viscoelastic moduli, and deformation resistance, by incorporating ingredient composition, temperature, shear rate, and applied stress. For products such as dressings, yogurts, and preserves, ML models can accurately predict shear-thinning behavior, yield phenomena, and related textural attributes under different deformation regimes.[152] Lee *et al.*[122] built an ML framework to predict the viscosity curves of various hydrocolloid solutions used in plant-based meat analogues. By tuning the network, their MLP achieved $R^2 \approx 0.994–0.996$ in predicting viscosity *versus* shear rate. Herrmann *et al.*[153] investigated the rheological behavior of 34 commercial food spreads, employing the Herschel–Bulkley model for their analysis. An artificial neural network (ANN) was trained to predict key rheological parameters, including yield stress, consistency index, and flow behavior index. Kwon *et al.*[154] explored the thermal–mechanical properties of wheat flour and the rheological characteristics of noodles using ML approaches, resulting in a novel framework for predicting noodle stretchability. Mishra *et al.*[155] trained a nonlinear autoregressive neural network on a single shear test of yogurt. The ANN learned the full thixotropic and viscoelastic response: it predicted yield-stress, hysteresis loops, and creep behavior with over 92–98% accuracy. Jiang *et al.*[156] established the relationship between near-infrared spectra of frozen samples and drip loss, texture parameters (including hardness, chewiness, adhesiveness, and gel strength) using ML, enabling the prediction of quality indicators of frozen samples without thawing. Overall, these predictive models substantially enhance structure-driven texture design, product development efficiency, and the rational selection of processing and storage conditions. By leveraging ML, researchers can significantly reduce the time and resources required for traditional empirical experimentation.

The efficacy of 3D printing processes is significantly influenced by rheological properties, particularly yield stress, viscoelasticity, and shape-retention ability. These properties collectively define the printable texture window and final product quality. By applying ML to predict these properties, we can precisely control 3D printing processes and optimize printing parameters, thereby enhancing both product quality and printing accuracy. In a pertinent study, Tang *et al.*[137] integrated low-field nuclear magnetic resonance data with ML to develop a predictive model that links the rheological properties of polysaccharide solutions with their 3D printing suitability, enabling an intelligent assessment of printing processes. Outrequin *et al.*[135] combined rheological analysis with ML to investigate how network characteristics and processing parameters on the distribution of 3D printing filaments. Maldonado-Rosas *et al.*[157] constructed the printability of formulations with different starch compositions and printing temperatures during the 3D printing process using a Gaussian process regression model. This integration has advanced customized food printing by enabling precise control of overflow, deformation, and solidification-related texture, thereby improving structural fidelity, sensory quality, and manufacturing efficiency.

4.3 Real-time monitoring and production process optimization

An ML approach can be readily integrated into food production processes, enabling real-time monitoring and intelligent regulation of rheological and texture-related properties, while optimizing workflow efficiency and production stability. Its application within the culinary sector demonstrates significant potential for enhancing productivity, precision, and overall operational intelligence.

In food manufacturing, ML systems leverage high-accuracy sensors and analytical instruments to monitor process variables in real time and predict rheological responses and texture attributes, such as viscosity evolution, firmness development, and structural consistency. This instantaneous predictive capability enables production lines to rapidly respond to data shifts and automatically adjust processing parameters, such as shear rate, temperature, and pressure, to maintain stable flow behavior and consistent texture-related mechanical properties throughout production.[158] Implementing a real-time control system powered by ML allows production lines to minimize human intervention and reduce financial losses arising from quality variations.

ML proves particularly effective in optimizing complex processing stages where rheological evolution directly influences texture formation, such as during mixing, heating, cooling, and shaping. In rice flour and cheese production, ML algorithms can be employed to quantify how individual steps (mixing, heating, cooling, and shaping) influence rheological parameters that directly determine texture, including gel firmness, cohesiveness, and resistance to deformation.[4,127] Based on these analyses, the model can identify optimal combinations of processing conditions that concurrently stabilize rheological behavior and achieve desired texture attributes, while also minimizing energy consumption, raw material waste, and process variability. By utilizing comprehensive multivariate data analysis, ML can predict potential production bottlenecks and risks of texture instability, such as excessive softening, structural collapse, or inconsistent firmness, thereby providing valuable decision support for process optimization.

The integration of ML technology into food creation not only enhances process efficiency but also propels the field towards greater productivity, increased eco-friendliness, and the development of novel innovations. This technological convergence has paved a new path for growth within the food industry.

4.4 Sensory evaluation

The sensory attributes of food, such as mouthfeel, smoothness, chewiness, and firmness, are closely linked to its rheological properties. By employing ML techniques to jointly model rheological measurements and sensory evaluation data, food sensory performance can be systematically optimized, enabling more accurate alignment between material behavior, perceived texture, and consumer expectations. Jeong *et al.*[114] took rheological test results as inputs and trained a TensorFlow logistic classifier. The model separated foods into “elderly-friendly” and “not” with 98% accuracy.

ML approaches can directly link sensory evaluation data and rheological test outcomes, allowing for regression-based predictions of sensory attributes from quantifiable texture-related rheological parameters. These models can accurately predict perceived smoothness, firmness, and ease of deformation based on rheological characteristics such as viscosity, yield behavior, and viscoelastic moduli.[76] Dimassi *et al.*[159] established grading criteria for kishk (a dry fermented cereal-dairy product) based on sensory attributes using a decision tree model. These criteria can be applied to control the product stability and quality of kishk. Consequently, food scientists can optimize product formulations at earlier stages of development, thereby minimizing trial-and-error processes and enhancing both efficiency and accuracy. Repeated model refinement improves prediction accuracy, providing increasingly reliable guidance for the optimization of sensory attributes.

By combining consumer feedback and comment data, ML performs sentiment analysis to gain a deeper understanding of consumer reactions to food items' rheological characteristics and sensory experiences. The sentiment analysis approach extracts consumer preferences and needs regarding item texture, flavor, and appearance, guiding formula creation and refinement. Ge *et al.*[160] summarized the latest advances in ML models for predicting and modulating food flavors. By integrating rheological properties with existing data, companies can enhance the customization of food creation, resulting in products that better serve target consumers' desires.

5. Challenges and future outlooks

While ML holds significant potential for advancing food rheology, its implementation within industrial production encounters substantial challenges. The effective execution of real-time data collection and analysis necessitates further development and refinement. The computational efficiency and practical applicability of ML algorithms in industrial contexts remain urgent. Importantly, the limited interpretability of these models poses a barrier to their use in safety-critical areas, such as food quality control, thereby hindering their widespread adoption across the industry. Addressing these challenges requires enhanced expertise and training into food processing and research, enabling researchers, formulators, quality control personnel, and others to fully integrate ML technology in their daily operations.

Besides, data acquisition in food rheology poses substantial challenges due to its intricate and costly nature, which often leads to datasets that are limited in scope and inconsistent in quality. Furthermore, the rheological behavior of food materials is frequently characterized by pronounced non-linearity and intricate multi-relationships, posing difficulties for conventional ML models, which often struggle to accurately capture and interpret such nuanced behaviors. Moreover, variations in testing conditions and food systems exacerbate data modeling issues, necessitating the development of more robust models and sophisticated data augmentation techniques to enhance model accuracy. In addition, scaling up ML for industrial use raises significant concerns about computational cost and energy consumption: training and deploying large models in production can lead to a substantial carbon footprint, particularly if not optimized for energy efficiency. Texture analysis also presents unique challenges, as texture profiles obtained from specialized instruments involve complex, multidimensional data that further complicates ML modeling and interpretation. This energy demand can become a barrier for widespread adoption, especially for smaller food companies lacking high-performance computing infrastructure. Simultaneously, limited data volume and poor-quality measurements from small sample sizes further constrain model generalizability and robustness, highlighting the risk of overfitting and bias. Addressing these issues will require not only efficient algorithmic designs and green computing strategies but also concerted efforts to standardize data collection protocols, improve sensor reliability, and curate large, diverse, and high-fidelity datasets.

Future research will likely focus on intelligent information acquisition, multimodal data fusion modeling, and the development of more concise and interpretable mathematical formulations. By advancing transfer learning and generative adversarial network techniques specifically adapted for limited sample datasets, the applicability of models can be significantly expanded. Concurrently, personalized food formulation and the intelligent optimization of industrial production processes will facilitate deeper integration of ML into food rheology, thereby providing robust technical support for innovative concepts within the food industry.

Conflicts of interest

There are no conflicts to declare.

Data availability

The data supporting the findings of this review are derived from previously published studies, which are cited in the references section. No new primary data were generated in this review.

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