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A Structural Quality Model for New Product Development to Enhance Resilience in Closed-Loop Formulated Food Supply Chains

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Abstract

The rapid changes in the design and development of new food products in marketplaces increase the pressure and growing demand on Supply Chain Systems (SCS), necessitating a focus on reducing operational costs and enhancing response time efficiency to meet consumers' demand in New Product Development (NPD). Current research and development approaches involve a substantial volume of information concerning the desired attributes for product quality that align with consumer expectations. This introduces high uncertainty and potential risks within supply chain networks. In order to address these challenges, it is necessary to integrate modern communication methods and advanced manufacturing technologies. This integration takes the form of innovative tools, techniques, and models designed for the pre-processing, selection, and dimensionality reduction of the extensive amount of information and data associated with product quality attributes. Therefore, this research proposes a new structural quality model for designing and developing food products to reduce the independent variables affecting newly formulated food products and all other possible quality factors. As a methodology, Principal Component Analysis (PCA), combined with multivariate statistical techniques, is employed to enable quick and flexible responses to consumer demand through advanced food processing technologies. This assists in determining the optimum number of quality dimensions that affect the final formulations of new products produced at decentralised local markets. A real-life case study on formulated beverages was conducted in the UK, focusing on food-grade applications, and it aimed to identify strategies for reducing waste, uncertainty, and risk in food NPD through an optimised manufacturing process. The results indicate that the developed model offers a better option for management, enabling the integration of supply chain actors with formulation processes to achieve economic and sustainable benefits for a resilient supply chain.

Keywords: Food industry, New product development, Modelling, Multivariate statistical analysis, Formulated beverages, Supply chain systems.

1. Introduction

Modern supply chains are becoming increasingly responsive and sophisticated, driven by advanced information and communication technologies, stimulating rapid responsiveness and global interconnectedness such as the Internet of Things (IoT), Artificial Intelligence (AI), blockchain, and cloud computing [1,2,3,4,5,6,7]. These technologies improve supply chain visibility, streamline decision-making, enhance real-time responsiveness, and optimise information logistics flows through process automation for organisations to quickly adapt to changing consumer demands and market opportunities and ultimately improve efficiency in material flow movement and its operations [2,7,8,9, 10,11,12]. However, the food supply chain, crucial for human socio-economic development and security, has witnessed a growing adoption of modern technology within the processing industry. However, operational efficiency demands a continuous increase in speed to transport and improve food products, satisfying consumer expectations in terms of health, safety, sensory quality, and novelty [1,5,8,13,14,15,16,17,18,19].

The food processing industry plays a significant role in Supply Chain Systems (SCS), contributing to historical periods, product variety, and revenue. Due to uncertainties

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and leaps in SCS, challenges are associated with increased globalisation, just-in-time production and concepts, outsourcing, and shorter product lifecycles. A more efficient supply chain is imperative, necessitating risk management to address issues like single sourcing, low inventories, and increasing product complexity. Thus, food supply networks are required to be resilient and responsive to any disruptions, either natural or man-made factors such as weather changes and logistics challenges [8,20, 21, 22, 23,24,25,26].

Efficient and effective product design and manufacturing methods are crucial for Research and Development (R&D) departments within SCS functions [19,27,28,29,30,31]. Close collaboration between the NPD process and supply chain operations is necessary [32,33,34]. Decentralised approaches to R&D and manufacturing are more cost-effective and efficient than traditional coordination methods [35,36,37,38]. By adopting these approaches, SCS manufacturers can produce customised products focusing on minimum quality attributes while maintaining high quality. This ensures timely delivery of products, eliminates supply chain delays and breakdowns due to lead time, logistic or transportation issues, and enables manufacturers to create products that supply to consumer demands and market trends across different segments.

In this sense, the dynamic nature of supply chain systems and the rapid pace of new product development in the food industry emphasise the need for research to enhance the novelty of this study. Present-day SCS face obstacles like expensive operational costs, delays in response time, and significant uncertainties stemming from the amount of information needed for product quality attributes. The practical implementation of advanced communication and manufacturing technologies is essential in tackling these challenges, yet their application is deficient within the context of the food supply chain [8,19,25,26,39,40]. This research seeks to narrow the divide by suggesting a fresh structural quality model that utilises Principal Component Analysis (PCA) and multivariate statistical methods. This new method decreases the variables impacting new food products and improves quality dimensions, boosting the supply chain's overall resilience and sustainability. The study is supported even more by a tangible example, showing how it can be applied in real life and provide notable economic and environmental advantages.

Accordingly, this research proposes a new structural quality model for designing and developing food products to reduce the independent variables affecting newly formulated food products and minimise all other possible quality factors. The current research is within the context of formulated food products' manufacturing processing supply chain. It addresses several issues in the food supply chain system. These involve the necessity to handle health and safety concerns linked to food items and the ongoing supervision of their quality. Moreover, there are social restrictions on food production chains concerning the efficient use of economic resources, following safe production methods, and adhering to environmental impact guidelines. Another critical issue is the vulnerability to supply interruptions, requiring a robust supply chain system. The paper also highlights the importance of implementing a structural quality model in fresh product creation for overseeing supply chain tactics and adaptability, duplication, and handling uncertainty, especially in times of crisis such as natural calamities and the COVID-19 outbreak. The suggested approach is novel for merging PCA and Structural Equation Model (SEM) with Confirmatory Factor Analysis (CFA) to construct and verify the structural quality model. This new method aids in decreasing the complexity of physical, chemical, and sensory characteristics, making it easier to pinpoint important quality aspects. The model considers sensory and physical properties, thoroughly assessing quality attributes in formulated beverages.

The suggested approach framework consists of three separate phases. The initial phase includes choosing the desired product according to consumer needs and wants, and making use of a sophisticated production system. The next phase is dedicated to pinpointing and measuring the physical, chemical, and sensory characteristics of the created item using analytical tools and Quantitative Descriptive Analysis (QDA). The last step includes creating a new structural quality model utilizing PCA and SEM along with CFA to confirm and investigate the structure obtained from PCA outcomes. The research's main results show that six separate quality factors were determined to be essential for the overall quality of orange beverages: colour, overall acceptability, aroma, mean particle size (related to mouthfeel), physical stability percentage, and apparent viscosity. The PCA was utilized to simplify data and pinpoint key attributes, while the SEM confirmed the relationship model constructed based on these attributes. The results of the model fit showed excellent fit with different indices, indicating the strength of the developed structural quality model. This model can be used in the initial phases of new product development to guarantee top-notch products that align with consumer preferences and can be customized for various decentralized regional markets. Hence, The research’s contributions are summarised as follows:

- Developing a quality structural model for formulated food products in process industries was validated through an empirical statistical model. This model explains the essential products and manufacturing attributes of newly formulated products to meet desirable consumer requirements.
- Proposing a methodology integrating statistical experimental design with principal component analysis. This approach is employed to estimate, prioritise, and eliminate uncertain risks or incidents related to safety and health hazards, raw materials shortages, or high costs expected during the formulation design process.
- Introducing an advanced, continuous, automated, integrated product\process formulation platform as a lab-scale formulation processing technology.
- Provision of decision-making guidance for R&D departments and managers in selecting raw materials suppliers and choosing cost-effective, safe, and healthy ingredient concentrations. This guidance is based on early consumer involvement during the product design process.

The rest of the paper is organised as follows: Section 2 presents the theoretical background of food SCS and food product characterisation regarding its physicochemical and sensory properties and consumer acceptance. The development of a structural quality model accompanied by statistical analysis techniques employed in this research and supported by a real-life case study is discussed in Section 3. Section 4 presents results and discussion based on a real-life case study of a formulated beverage to identify minimum quality factors affecting its production process. It ultimately proposes the developed NPD model within SCS, particularly beverage formulations. Then, it is followed by the main conclusions and future works in the last section.

2. Theoretical Background

From a strategic viewpoint, food and beverage products are considered a strategic, modern, and strongly market-driven industry. For example, in European countries and the UK, the food and soft drinks industries constitute the largest production sector in size and turnover, comprising 13.6% of the overall food production industry. This translates to a substantial financial impact, with figures reaching £16.5 billion and €799 billion, depending on the country [26,41,42]. As a result, food products are regarded as the final phase of SCS, which starts with agricultural and marine production and ends with consumers utilising the products in different ways. According to the researcher [43], the technology of food products involves systematic and controlled activities to preserve, transform, create, or destroy a structure that results from natural processes or human interventions. The next sections will discuss the food supply chain systems, food product characterisation in terms of physicochemical and sensory properties and consumer acceptance.

2.1. Food Supply Chain Systems

Food Supply Chain Systems (SCS) are globally interconnected chains that have multiple relationships to satisfy consumer requirements, including product variety with competitive prices and desirable qualities [2,16,44,45,46,47]. Due to technological development in food supply chains, their overall performance has improved dramatically in recent years [38,46,48,49]. Examples of such development include innovative advanced technologies, new open markets, consumer demands with specific quality attributes, and geographically diverse innovative products [45,50,51,52]. Nevertheless, several growing challenges are highly demanding in controlling the overall performance of the food supply chain. Such challenges, from the first stage to the end stage of the food supply chain, encompass health and safety issues related to food products and continuous quality control [44,53]. On the other hand, food production chains also have several constraints from society, including economic resource utilisation, safety production practices, and environmental impact limitations [16,50,54,55]. Thus, while the food supply chain represents a unique and attractive component of SCS, it shares similarities with pharmaceutical process industries regarding susceptibility to supply disruptions [56,57]. The potential for such disruptions or unexpected risks necessitates resilience to improve capabilities and simultaneously mitigate vulnerabilities in SCS in the context of manufacturing process industries [20,22,23]. Significantly, supply chain resilience directly affects more than 80% of global firms due to the globalisation of operations and the insatiability of market production [57].

Resilience in SCS necessitates a proactive approach that addresses its inherent multidimensionality and complexity. As a result, the manufacturing supply system must be designed to consider the dimensions of resilience and sustainability, encompassing capabilities and vulnerabilities. Several studies by earlier researchers shed light on these dimensions to effectively respond rapidly to uncertain fluctuations and disruptions in the supply chain. These elements include flexibility, visibility, redundancy, collaboration, trust, velocity, market adaptation, contingency planning, innovation, cost, and response effort [20,21,22,23,57,58,59,60,61]. Flexibility, redundancy, and robustness are the key elements influencing resilience and sustainability. This enhancement makes SCS more sufficiently resilient, helping to eliminate vulnerability and minimise the potential impact of disruptions. Achieving this level of resilience requires collaboration and expertise from various scientific fields, including marketing, operational research, food process technology, economic science, and environmental science [54, 62, 63].

Additionally, this challenge entails decentralised approaches with a commensurate technology leap [64]. Many partners, sub-partners, and routes produce the finished goods or products. It is challenging to control the flow of products and information control simultaneously [50]. As a result of customer satisfaction and acceptability, R&D departments in any organisation must be oriented toward innovation to create continuously innovative products [17,65]. Supply chain stakeholders play a pivotal role in designing and developing the process of final food quality. More importantly, customer satisfaction is related to product qualities that are influenced by various variables, categorised into intrinsic and extrinsic characteristics, ultimately impacting the final product quality. As previously mentioned, consumer expectations and perceptions of food products are pivotal factors in the food SCS, which aims to produce items that align with consumer requirements, emphasising mass customisation. Therefore, intrinsic, and extrinsic factors are crucial in understanding consumer preferences [66,67]. Intrinsic factors include appearance, taste, and other food sensory attributes. These factors are connected to the physical and chemical characteristics of the food structure and its sensory aspects [66]. On the other hand, extrinsic factors, including brand name, price, and other external personal influences, also significantly impact perceptions [63,66].

It is worth mentioning that the food and beverage industry must respond rapidly to meet evolving consumer desires and demands at a fast and flexible pace [68]. The Researcher [69] emphasised that it is essential for consumers' rapid response to utilise quantitative measures in sensory evaluations and to provide simple methods. Thus, consumers' critical dimensions in product acceptance in markets are food preferences connected to many interrelated elements [70] and sensory features such as appearance, flavour, and texture. The design and development of top-quality food products represent a complex endeavour that integrates process conditions, product properties, and consumer requirements. Identifying the most significant factors influencing the final product quality becomes crucial. This requires dedicated research and development efforts to pinpoint the primary factors shaping product quality, ultimately streamlining both time and costs in the design and development of the final product and its characterisation process.

2.2. Food Product Characterisation

The crucial issue in food product design to characterise finished products is to make the desired products successful in meeting customer requirements [65,71]. This issue is considered a multidisciplinary problem. An N-component mixture of ingredients is involved in the product design stage to introduce a new product with desirable properties for various food products [72,73]. However, using computer-aided techniques could be a helpful tool for the product design process to be more efficient and quicker. This practice is done by carefully identifying and selecting product problems and applying suitable product models in the food industry [74].

Conversely, different groups of consumers with diverse education, experience, and personal senses can define food products' desirable quality attributes. These properties could be eventually translated into measurable quality attributes in terms of sensory and physicochemical properties as a list of candidates for these attributes [42,71,75]. For example, process conditions play a significant role in the food product microstructure related to sensorial and physicochemical properties [42,76]. Thus, a central concern is linking food products' physicochemical and sensory properties to the food structure.

2.2.1. Physicochemical Properties of Food Products

Food properties are highly demanding for the product and process design in the food and drink industry (e.g. food technologists) for several reasons, including food handling systems, product features, consumer preferences for certain products, and food safety [77]. Food properties that are connected to physical and chemical properties are called physicochemical properties. Physical properties are classified into four categories affecting the food composition and structure [43,77]:

- Mechanical properties, including structural, geometrical and strength attributes.
- Electrical properties, including conductivity and permittivity attributes.
- Thermal properties, including specific heat, thermal conductivity, and diffusivity attributes.
- Optical properties, including colour, gloss, and translucency attributes.

The food products' physicochemical properties are characterised and evaluated to determine the intended final product's identity. These properties include density, viscosity, titratable acidity, mean particle size, physical stability, refractive index, water activity, and conductivity (Intertek, 2019). Experience in the field has shown that physical properties such as viscosity, water activity, and pH may elucidate why mouthfeel variances occur. For instance, regular cola carbonated beverages and diet cola carbonated beverages are meaningfully altered in terms of mouth coating, body, and astringent properties due to sensory and physical properties.

Understanding customer requirements and desires is essential in determining the final properties of food product quality engineering (i.e., physical, or physicochemical properties) [55, 78]. In this regard, analytical methods, or measurements of these attributes (i.e. quality control) are necessary to provide quantitative information about the effect of process and product conditions on food product structure and microstructure [69,75]. This information could also help mathematical models based on several experiments [52]. Concerning cost trade-off in the food industry, quality control and evaluation of food product quality attributes cost roughly 1.2-2.0% of the total sales of food products yearly [79]. Thus, reducing the quality attributes of the food product within R&D work is imperative to be effective and efficient.

2.2.2. Sensory Properties of Food Products and Consumer Acceptance

Consumer identity could be determined by focusing on consumers' sensory attributes and perceptions of certain sensory proprieties of the food products. Therefore, food products' sensory properties, such as texture, appearance, taste, and flavour, are essential for the overall product quality and consumer acceptability [80,81]. A prominent example of the food and drink industry is developing a new product obtained by changing existing food products' appearance, flavour, and texture attributes rather than altering the main core ingredients [82].

Sensory properties of food products could be assessed and evaluated using different instrumentations to provide quantitative information, as well as the results of some specific sensory properties. These instrumentations are required to develop sensory profiles using trained panellists in descriptive analysis methodologies, which is a very costly method [81]. Hence, quicker, simpler, and cheaper instrumentations such as quantitative descriptive analysis are more desirable for sensory evaluations [81,83]. From a consumer viewpoint, a specific sensory quality attribute is needed, and therefore, acceptance or rejection of the food products in markets is based on their sensory properties. This creates a high chance of product success in the markets (i.e. product acceptability). The degree of acceptance depends on three types of consumer perspectives: food characteristics, consumer characteristics, and consumer environment [81]. In this sense, food product acceptance is regarded as a multidimensional process linked to many factors besides the sensory attributes of food products alone [70, 83]. Furthermore, the human sensory system is highly sensitive, but slight product differences are challenging to recognise. As a result, trained panellists and quantitative descriptive sensory analysis are employed in evaluating and quantifying the desirable sensorial food properties [69].

2.3. Research Significance and Motivations

Unlike earlier researches, this research introduces a unique structural quality framework for creating formulated food items. The researcher [4] focused on the drivers of blockchain implementation in supply chains using Interpretive Structure Model-Cross-Impact Matrix Multiplication Applied To Classification (ISM-MICMAC) analysis from a dynamic capability viewpoint. This research concentrates on developing an empirical statistical model to improve product quality and mitigate risks in the formulation design process despite discussing modern supply chain systems and efficiency. It broadens the idea of incorporating cutting-edge technologies into supply chains, such as the study [4] of blockchain. However, it focuses on applying this to practical uses in food product development through a continuous automated, integrated product/process formulation platform to improve operations and meet consumer needs. Also, researchers [1,5] focused on choosing environmentally friendly suppliers using the Internet of Things (IoT) and a Combinatorial Multi-Criteria Decision-Making (CMCDM) method, highlighting sustainability and supplier selection.

As a result, our research explores supplier selection using empirical statistical models instead of IoT and MCDM, setting it apart in methodology. Cutting-edge technologies like statistical experimental design and principal component analysis enhance product quality and address risks in the food processing supply chain processes. The researcher [5] proposed designing a multi-echelon agri-food supply chain network that combines operational and strategic goals in India's public distribution system. Contrary to Gupta et al.'s focus on optimising supply chain network design for efficiency and strategic alignment, our research concentrates on product quality and process efficiency within food product development. It expands on enhancing supply chain operations by presenting a framework for improving product quality, integrating aspects of strategic supply chain management tailored to the unique issues of food product development and meeting consumer needs.

In the literature above on supply chain resilience and improved SCS, limited studies have developed quantitative empirical models to manage supply chain practices and resilience, mainly focusing on flexibility and redundancy. Most of these studies primarily focused on qualitative approaches, using conceptual and theoretical resilience frameworks and models to identify the resilience elements rather than the quantitative ones; hence, this paper's aim was established. The development of quantitative empirical models to effectively manage supply chain practice is still not mature. Therefore, it is necessary to incorporate quantitative approaches to complement qualitative frameworks and understand the resilience of supply chains. This understanding will enable management strategies for building resilient supply chains. Additionally, a structural quality model for new product development can improve managing supply chain practices and resilience, focusing on flexibility, redundancy, and coping with uncertainty by addressing challenges such as employee shortages and food transportation issues under risks and uncertainties in formulated food supply chains. By integrating these insights, a comprehensive framework can be formulated to evaluate factors that influence resilience and suggest effective strategies for mitigating disruptions in closed-loop formulated food supply chains, ultimately enhancing their overall resilience and ability to adapt to unforeseen challenges to enhance product quality.

3. Methodology

This research presents a new quality model to improve NPD's robustness in closed-loop formulated food supply chains. The method combines modern manufacturing technologies with advanced communication methods, utilising PCA and multivariate statistical techniques. In this way, it confronts the complexities and uncertainties in food supply chains, improving product quality characteristics and simplifying the development process. The methodology's effectiveness is confirmed by a practical example involving formulated beverages in the UK, showing how the model successfully minimises waste, uncertainty, and risk while delivering economic and sustainable advantages.

3.1. Design of The Proposed Methodology Framework

The methodology framework proposed incorporates three distinct stages. The initial stage entails the selection of the target product to be formulated, which is based on the demands and desires of consumers, utilising an advanced manufacturing platform. Subsequently, the second stage involves the identification and quantification of the physicochemical and sensory properties of the formulated product. This is achieved using analytical instruments for physicochemical measurements and consumer preference assessments through Quantitative Descriptive Analysis (QDA). The third stage focuses on developing a novel structural quality model for the formulated product. This is accomplished by employing multivariate statistical analysis to reduce the dimensionality of the physicochemical and sensory properties. In this study, PCA was used in conjunction with a statistical experimental design for factor analysis.

Furthermore, Structural Equation Modelling (SEM) utilising the Confirmatory Factor Analysis (CFA) technique was employed to validate and examine the structure derived from the PCA results. The design of the proposed methodology framework used in this research is depicted in Figure 1. The research design was carefully planned by incorporating various statistical analysis methods to guarantee a thorough assessment of orange drink quality characteristics. PCA was utilised to decrease the dimensionality of the physicochemical and sensory properties, making it easier to pinpoint the most critical quality factors. This decrease was significant in handling the dataset's complexity while holding onto vital information. Following this, SEM with CFA was employed to confirm and explore the connections between the quality characteristics identified from the PCA. Before analysing their structural relationships, this method guaranteed that the constructs were valid and reliable. Response Surface Methodology (RSM) was used in the experimental design to investigate different ingredients and process parameters, guaranteeing the creation of top-notch formulated products. Combining these statistical techniques established a solid foundation for creating a structural quality model that effectively represents consumer preferences and product attributes.

The following sections provide more information about the materials and methods used.

3.1.1. Multivariate Statistical Analysis

Multivariate statistical analysis involves techniques to analyse and interpret patterns within multivariate datasets. This area of research specifically focuses on two widely used techniques, namely PCA and SEM with CFA. The

CFA approach serves as a crucial component within SEM, which is used to validate the measurement models associated with latent constructs and examine whether observed variables accurately reflect the underlying factors. In this context, CFA tests hypotheses about the relationships between these variables and the latent constructs they are hypothesised to measure. Moreover, CFA establishes the measurement quality of latent constructs, which is foundational before dealing with the structural relationships in SEM. By conducting CFA first, researchers can confirm that the identified constructs are valid and reliable. This process helps avoid common pitfalls such as measurement error and model misspecification, yielding more trustworthy results in causal inference and hypothesis testing within SEM frameworks. Thus, These powerful tools aid in identifying patterns, validating structural relationships, and modelling involved interactions among variables in multivariate datasets. The following sections discuss these techniques.

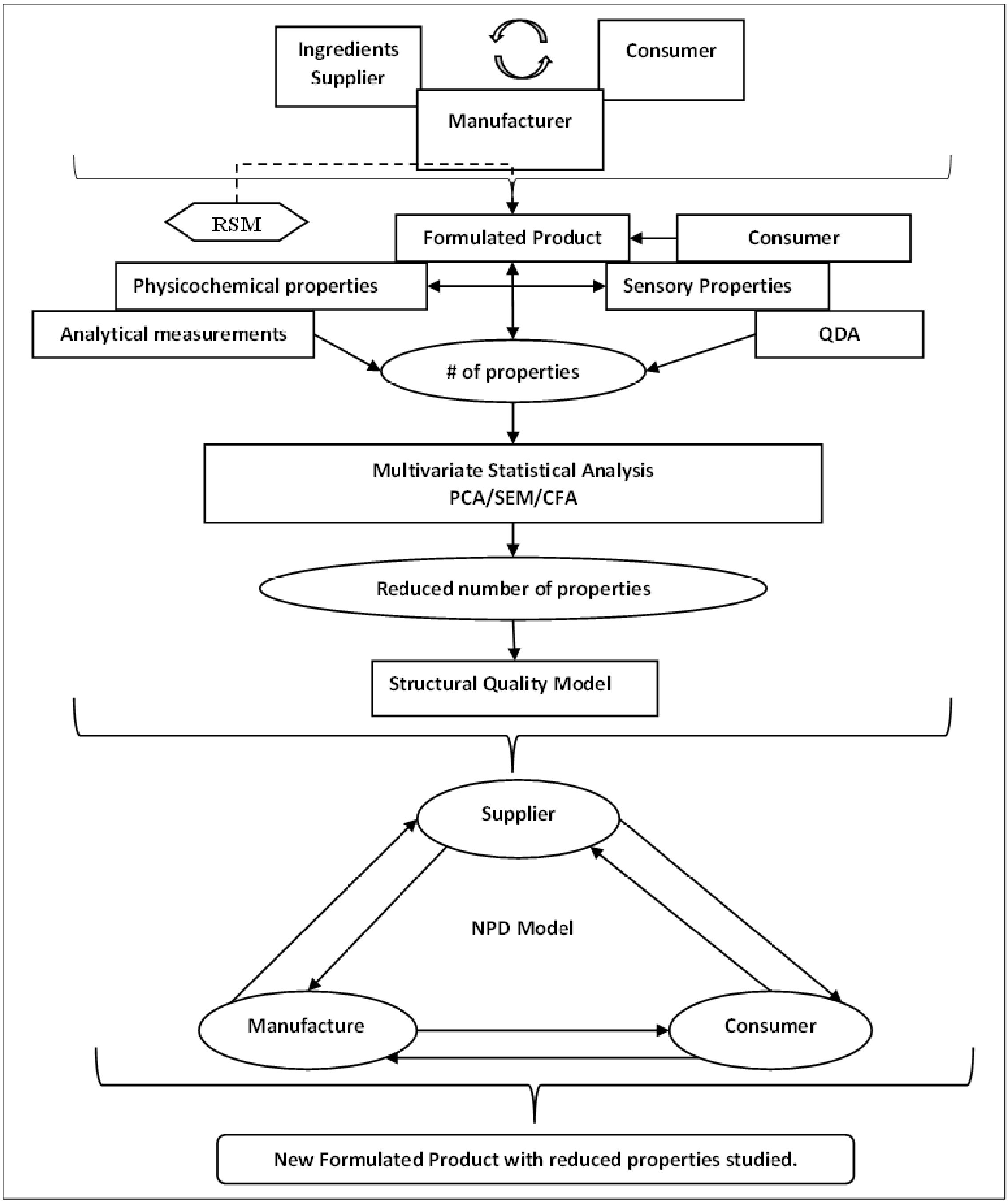

Figure 1. The proposed methodology framework.

- **Principal Component Analysis**

Principal Component Analysis (PCA) is an exploratory technique that aids in recognising and presenting patterns in multivariate datasets. The measurable characteristics of orange beverages obtained from the conducted experiments were subjected to multivariate statistical analysis using the IBM statistical package software SPSS (Version 25). The usage of PCA in the statistical analysis aimed to understand the interrelationships between the various measurable characteristics of orange beverages. In this context, factor analysis based on PCA was employed to determine the most significant factors that impact the final quality of the beverage product, thus reducing the number of quality factors studied to a smaller set of artificial quality attributes.

In addition to providing a general overview of PCA, a crucial aspect was calculating the magnitude and direction of the existing interrelationships between the measured quality attributes of orange beverages and the values of the linear correlation coefficient. Subsequently, the null hypothesis was tested using the t-student test at a significance level of 0.05. The hypothesis posited that no statistically significant difference exists between the correlation coefficient values (i.e., population(ρ)= 0). The statistical analysis also unveiled further insights regarding the principal components through an orthogonal transformation of the multidimensional quality factors studied, which reduced the spatial relationships among the attributes of the beverage's quality. PCA entails an orthogonal transformation of related quality attributes into linearly independent PCs to reduce dimensionality and reveal perceptions within the data. At this stage, the orthogonal transformation is a linear transformation depicted by an orthogonal matrix to guarantee that the transformed quality attributes remain uncorrelated. Hence, its purpose is to reduce the dimensionality of the dataset while preserving as much variance as possible. By employing the orthogonal transformation, PCA seeks to recognise a new PC that encapsulates the utmost variability within the data, thereby reducing redundancy and enhancing interpretability in fewer dimensions. The PC obtained through orthogonal transformations can be interpreted as directions in which the data varies the most. Changing the basis of the data to this new PCA allows the most critical features to be emphasised while maintaining the orthogonality of the components, making them uncorrelated. This structured approach aids in visualising and analysing complex datasets more effectively. Thus, the new measurable quality factors (i.e., the principal components) represent linear combinations of the initial quality attributes and account for the total variance of these attributes. By ordering the PCs based on variance, the first PC captures the most variation in the original data, offering a comprehensive understanding of the underlying patterns and relationships among the variables. This transformation results in a more manageable data representation, facilitating more straightforward interpretation and analysis across various quality attributes.

- **Structural Equation Modelling**

Structural Equation Modelling (SEM) is a more extensive approach which uses factor analysis and path analysis to model complex relationships between observed and latent variables. The CFA technique was applied to validate the structural model of quality factors derived from the PCA procedure. In order to execute this analysis, the SPSS Amos 23 software package was exploited. Consequently, the conceptual framework of quality attributes, utilising SEM through CFA, was employed to validate further and investigate the structure derived from the PCA results. In this study, the structural model was validated through convergent and discriminant validity to either confirm or reject the model. Convergent validity is indicated by high loadings of indicators on their respective latent variables, whereas discriminant validity ensures that constructs are distinct from one another and not highly correlated. The successful assessment of these tests contributes significantly to establishing the overall construct validity of the SEM Model.

3.1.2. Statistical Experimental Design

The experimental design space was developed by implementing a series of experimental runs using Response Surface Methodology (RSM) based Central Composite Design (CCD). It was based on a few previous studies [9, 37, 85]. The primary objective of these studies was to explore the various ingredients and process parameters that could be utilised in a scalable continuous-flow manufacturing platform to produce a wide range of formulated products that possess diverse sensory and physicochemical properties.

3.1.3. Instrumental Analysis

Analytical methods were used to determine the physicochemical properties of the formulated product to obtain quantitative information about the product attributes. The quality attributes of orange drinks (sensory and physicochemical properties) were studied to obtain a quality structural model of consumer-driven orange drinks in the food SCS. The physicochemical properties studied were viscosity, viscosity ratio, mean particle size, pH, electrical conductivity, physical stability, and density. Triple measurements for each attribute were averaged and recorded using specific analytical methods.

3.1.4. Quantitative Descriptive Analysis

In addition to the orange drinks' physicochemical measurements, the sensory assessment was carried out to identify the consumer preference level of the most preferred sensory attributes of the orange drinks. For this purpose, Quantitative Descriptive Analysis (QDA) was carried out with untrained consumer panels. The untrained consumer panels of 250, with different geographical backgrounds such as nationality, gender, and age, were designated to taste and evaluate orange drinks regarding sensory properties. The sensory properties are appearance (i.e. colour intensity), flavour (i.e. smell), texture (i.e. smoothness), taste (i.e. acidity) and overall acceptability. Regarding drink products, colour, flavour, and taste are the most important sensory attributes that impact consumer preferences or acceptance [85,86]. These descriptors are the most familiar words in terms of consumer choice. Interval-based questionnaires using a scale ranging from 0 to 10 (i.e. a 10-point Likert scale) were constructed for the sensory evaluation process. Consumer responders (n= 250) were asked to draw an ellipse to assess their perceptions of the sensory attributes studied.

3.1.5. Samples

The experimental material was orange-flavoured beverages. Flavoured beverages in concentrated or diluted products are prominent emulsions in the soft drink industry. The flavoured beverage includes an oil phase, including flavouring agents, sweeteners, colouring agents, stabilisers, and water phase ingredients [85,86]. During beverage production, a combination of the ingredients and process parameters significantly influences the final formulated product's taste and other sensory and physicochemical properties. Consumer engagement and control of the measurable physical beverage attributes during production are effectively needed, regardless of the many critical constraints associated. However, the orange-flavoured beverage was chosen as the most widely consumable and profitable product in the soft drinks and formulation industry [37,86].

Twenty orange-flavoured juices were manufactured with different orange oil concentrations based on the CCD procedure. Each sample was made of the following food ingredients: water, gum Arabic, xanthan gum, and orange comminute from concentrate; citric acid, sodium benzoate; natural sweetener: maltodextrin, steviol glycosides; and natural food colour: beta-carotene. These ingredients were food-grade ingredients mixed in the continuous flow manufacturing platform under different ingredient concentrations (%w/w) and various process parameters (net flow rate (ml/min), amplitude (mm), and oscillatory frequency (Hz)) [9,37,85]. However, similar ingredients are available in commercial orange drinks and supplied by different SCS partners in the UK market.

3.2. Structural Quality Model of Formulated Products

In order to create a high-quality product that fulfils consumer preferences and desires, a new structural quality model is developed by identifying a set of key quality attributes. Through the collaboration between NPD and SCS teams, these attributes are chosen based on a combination of physicochemical and sensory factors. By carefully selecting the most critical properties and using the research methodology discussed in this section, the teams can streamline the product development process while maintaining the highest level of quality. This new structural quality model can be employed during the early stages of NPD activities and is suitable for application in various decentralised local markets. Figure 2 illustrates the development of the new structural quality model of formulated products by selecting the optimum number of quality properties studied. Thus, the literature review on food product design and development (e.g. case studies, relevant academic journals and guidance provided in the design research) shed light on the importance of incorporating powerful methods such as statistical experimental design, multivariate statistical analysis and quantitative descriptive analysis to create a systematic approach for designing and developing new food products. Additionally, integrations of scientific Knowledge and field experiences in demonstrating a real-life food formulation in the food and beverage industry were employed to develop and tailor food products to specific needs, focusing on food quality attributes to enhance consumer acceptability and satisfaction. These studies collectively contribute to delivering this structural model design in the food and beverage industry by integrating diverse approaches and technologies to meet consumer demands and improve product quality.

The PCA procedure is particularly suitable for reducing dimensionality in this context because it simplifies complex data sets by transforming them into uncorrelated variables called principal components. This reduction facilitates the identification of key quality attributes in NPD, enhancing the efficiency and accuracy of decision-making processes. The SEM, however, is appropriate for validating the structural model as it allows for the simultaneous examination of multiple relationships among variables. This capability is crucial for assessing the interactions and dependencies within the proposed quality model, ensuring its robustness and validity in addressing the challenges of resilience in closed-loop formulated food supply chains.

Integrating PCA with multivariate statistical techniques within the proposed structural quality model provides a robust framework for managing the complexities and uncertainties in NPD for formulated food supply chains. The PCA reduces dimensionality, simplifying the vast array of quality attributes by identifying the most critical variables. This reduction enhances the efficiency and accuracy of subsequent multivariate analyses, which can be employed to discern patterns, relationships, and impacts of various quality factors on the final product. These complementary methods streamline the data processing workflow, facilitating rapid and flexible responses to consumer demands. Additionally, by minimising the independent variables and focusing on essential quality dimensions, this approach helps optimise manufacturing processes, reduce risks, and improve the overall resilience and sustainability of the supply chain.

The structural quality model presented in the research for NPD in formulated food supply chains can be adapted or extended to other types of formulated products within the food industry by leveraging its core methodology of integrating modern communication methods and advanced manufacturing technologies. This approach utilises PCA combined with multivariate statistical techniques to manage the extensive data associated with product quality attributes, enabling quick and flexible responses to consumer demands. Applying this methodology to various formulated products, such as nutritional supplements, functional foods, and dairy alternatives, can achieve the same principles of reducing independent variables and minimising potential quality factors. This would involve tailoring the statistical models to these new product categories' specific characteristics and requirements, ensuring that the optimal quality dimensions are identified and controlled. Consequently, this adaptation would enhance resilience and efficiency across different food industry segments, ultimately leading to more sustainable and economically viable supply chains.

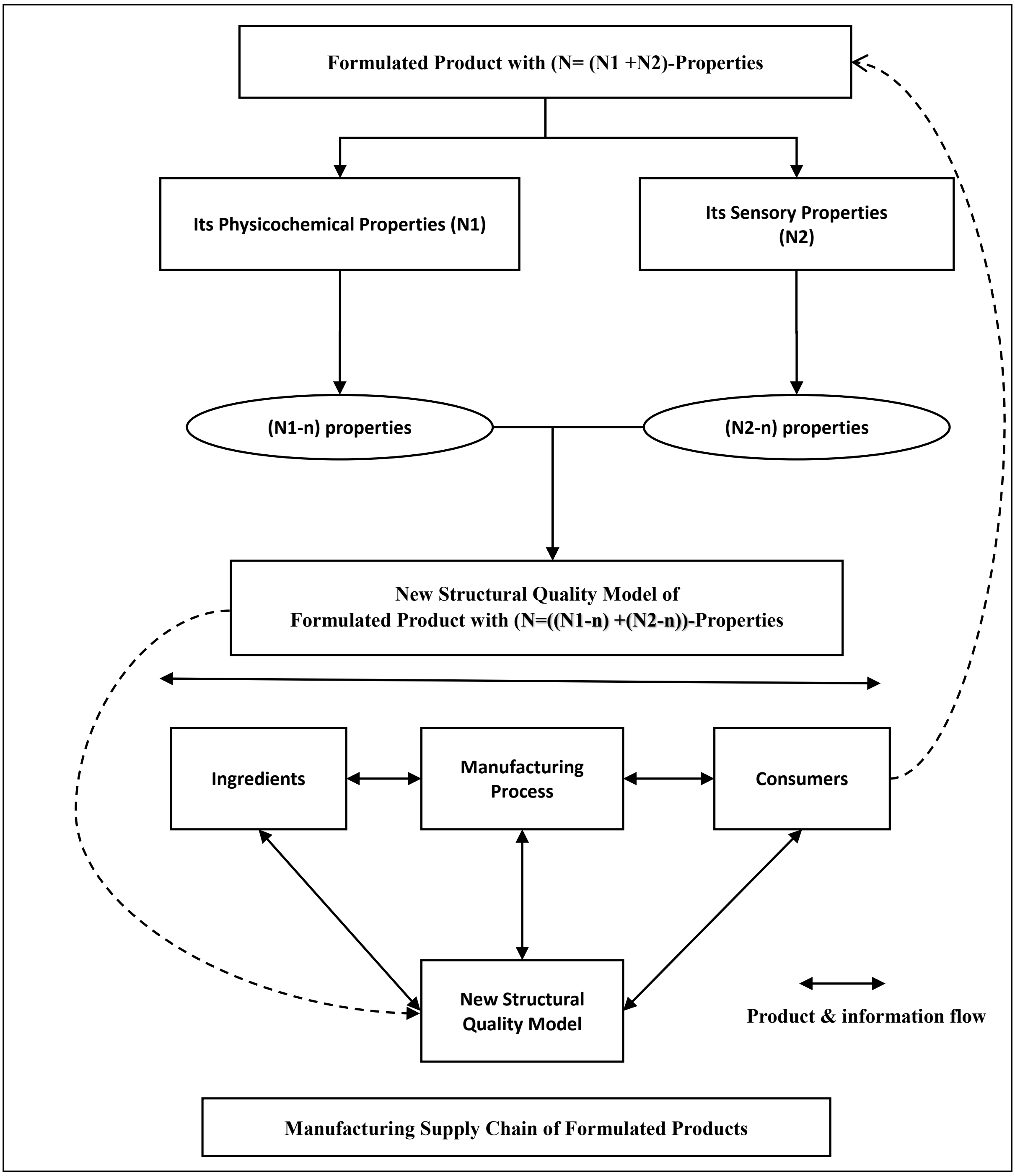

Figure 2. A Structural Quality Model of Formulated Products.

4. Results Analysis and Discussion

This research introduces a novel structural quality model to enhance the resilience of New Product Development (NPD) in closed-loop formulated food supply chains. By integrating advanced statistical techniques, specifically Principal Component Analysis (PCA), the model addresses the complexities and uncertainties in supply chain networks associated with consumer-driven product quality attributes. A real-life case study on formulated beverages in the UK demonstrates the model's efficiency in reducing waste, uncertainty, and risk, facilitating an optimised manufacturing process. The findings suggest that this model enables better integration of supply chain actors with formulation processes, ultimately achieving economic and sustainable benefits for a more resilient supply chain.

4.1. The Proposed Structural Quality Model of Formulated Beverages

In Figure 3, six independent quality factors were identified to represent the formulated beverage product from primary production (ingredients) to consumer consumption. These attributes instituted the recommended structural quality model to avoid redesigning or remanufacturing at early stages, and this approach could be employed in different decentralised local markets. The PCA was used to reduce the dimensionality of the data and identify the most significant quality attributes by transforming correlated variables into a smaller number of uncorrelated variables called principal components. This helped me to understand the key factors that impact the quality of the formulated product. Structural Equation Modelling (SEM), utilising Confirmatory Factor Analysis (CFA), validated the structural model developed from these attributes, ensuring the relationships between observed and latent variables were accurately represented and assessed for convergent and discriminant validity. Response Surface Methodology (RSM) based on Central Composite Design (CCD) was implemented to explore the interactions between different ingredients and process parameters, optimising the production process of the formulated product. Analytical methods were utilised to determine the physicochemical properties of the product, providing quantitative data on attributes such as viscosity, particle size, pH, and stability. This was complemented by Quantitative Descriptive Analysis (QDA) for sensory evaluation, where untrained consumer panels assessed the product's sensory properties, helping to link consumer preferences with product characteristics. Thus, The key factors that played a significant role in determining the overall quality of the orange drinks were colour, overall acceptability, smell, mean particle size (related to mouthfeel), physical stability percentage attribute, and apparent viscosity attribute. The initial step in the PCA process was to identify the critical quality attributes representing the overall quality of the formulated orange drinks, followed by the use of SEM based on CFA. Six key factors were examined in the CFA using SEM. The CFA employed the maximum likelihood method to statistically assess, test, and confirm the fit of the structural model for the quality factors under consideration. Measurement models were developed to explore the relationships between the six factors and their observed indicators, ensuring their validity before evaluating and testing the structural model.

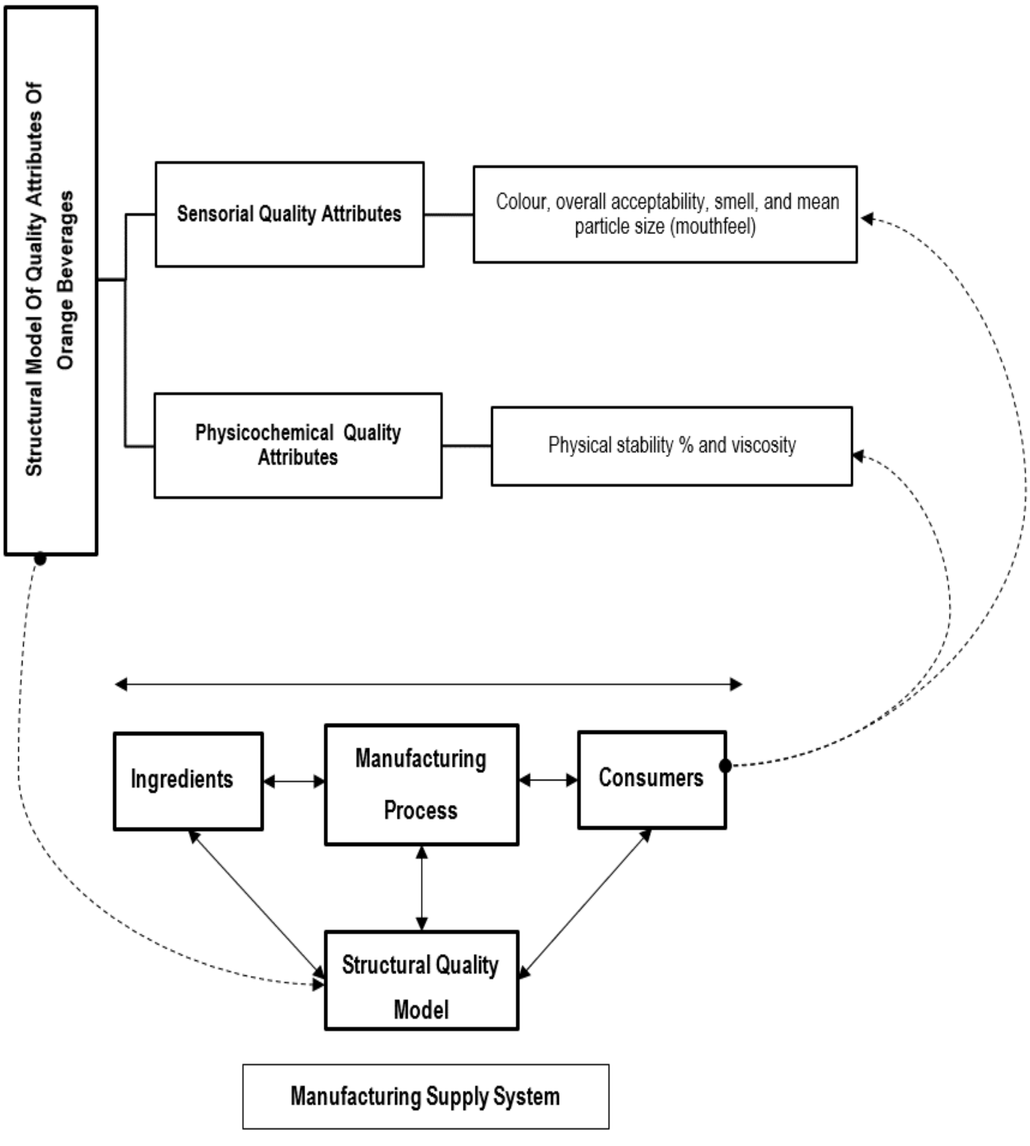

Figure 3. Structural Model of Quality Attributes of Orange Beverage Formulations

Consequently, based on the above, this research assumed that all the factors affecting orange beverage quality fit the PCA procedure. These six most significant factors were used with CFA using SEM. The CFA procedure using the maximum likelihood method was employed to statistically assess, test, and confirm the structural model's overall fit presented in terms of the quality factors examined. Measurement models with the underlying factors studies were designed to investigate the associations between the six factors and their observed indicators to establish their validities before evaluating and testing the structural model. The revised measurement models were improved and illustrated in Figure 4. The obtained results for the model fit are presented in Table I. The model fit results empirically indicated acceptable fit, as indicated by the fit indices: Normed Chi-square (CMIN/df), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker-Lewis index (TLI), Standardised Root Mean Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA).

Moreover, convergent and discriminant validity utilised the structural model validity, as presented in Table II. The convergent validity was designed to measure similar factors that are strongly correlated. In order to assess convergent validity, all factors' Average Variance Extracted (AVE) values were more than 0.50 for the first component factor. The second component factor could not be improved further, as only two factors were loaded onto it. Thus, convergent validity was maintained.

On the other hand, discriminant validity was evaluated by calculating the significant component factors of the square roots of the AVEs. These values for the first and second major component factors were 0.708 and 0.627 (respectively), higher than the correlation. Thus, it can be concluded that the factors' studied discriminant validity was achieved in the structural model, whereby they do not associate with different factors. Therefore, a more accurate structural quality model was established to identify correlations between main quality factors to uncover meaningful perceptions. This can inform improved decisions and save time and costs in the long term.

Ensuring convergent validity confirms that the attributes measured are related, while discriminant validity ensures that these attributes are distinct and do not measure the same underlying factor. This is essential in the context of the research on enhancing resilience in closed-loop formulated food supply chains. The proposed structural quality model relies on accurate and distinct measurement of product quality attributes to ensure the reliability and validity of the data. By confirming convergent and discriminant validity, the research can provide robust evidence that the identified quality factors accurately reflect different aspects of product quality and are not overlapping, which is crucial for developing effective strategies for new product development and supply chain resilience. This validation level helps minimise risks and uncertainties and ensures that the model can effectively guide decision-making processes in food product formulation and supply chain management.

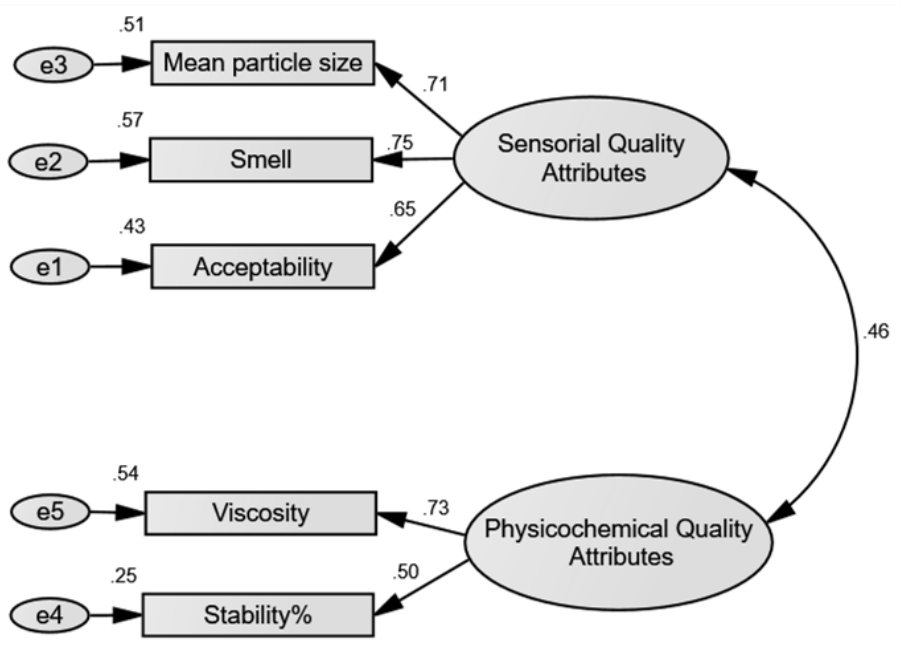

Figure 4. Structural Model of Formulated Orange Beverages

Table I. Model Fit Indices and Recommended Limits

No.	Fit measure	Value	Threshold	Interpretation
1	CMIN/df	0.460	≤ 3.0	Excellent
2	CFI	1	≥ 0.90	Excellent
3	TLI	1.5581	≥ 0.90	Excellent
4	IFI	1.138	≥ 0.90	Excellent
5	SRMR	0.066	≤ 0.08	Excellent
6	RMSEA	0.000	≤ 0.06	Excellent
7	PClose	0.781	> 0.05	Excellent

4.2. Structural Factors Determining the Quality of Formulated Orange Drinks

Principal Component Analysis (PCA) was employed to detect the significant quality factors affecting the formulated orange drinks. An initial step required for preparation and the data layout in the PCA procedure was to determine the mean and standard deviation of each quality attribute of orange drinks, followed by calculating values of the significant correlations between these quality attributes. In this regard, the statistical description of quality attributes of the formulated orange drinks (physiochemical and sensory properties) is presented in Table III, where the mean and standard deviation values were found to be different.

As shown in Table IV, a correlation matrix was employed to calculate the values of significant correlation coefficients of all the quality attributes studied in the orange drinks' formulations (emulsions) and their possible clusters. An indication for initial correlation and clustering of most of these attributes was found suitable (i.e. above 0.3). The obtained finding initially indicated four main factors for orange-formulated drinks, which are underlined, as presented in Table IV. The viscosity, viscosity ratio, mean particle size, pH level, and conductivity of the orange drinks were in the first group; the emulsion conductivity was in the second group. The third group included the density and physical stability of the emulsion. Thus, the PCA could be applied and proceeded further based on the initial results obtained.

Table II: Convergent and discriminant validity of the structural model

A. Convergent validity		
Latent Variable	**AVE**	
Principal Component 1	0.500	
Principal Component 2	0.393	
B. Discriminant Validity		
Latent Variable	**Principal Component 1**	**Principal Component 2**
Principal Component 1	**0.708***	
Principal Component 2	0.462**	**0.627***
* Squared Root of Average Variance Extracted (AVE) value. ** Correlation value between two principal components (1&2).		

Table III: Descriptive Statistics for Orange Drink Quality Attributes

	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Viscosity	0.01	0.05	0.0226	0.00228	0.01021	0.000
Viscosity ratio	0.97	3.13	1.6925	0.14822	0.66288	0.439
Mean particle size	4.18	14.00	6.8007	0.65778	2.94169	8.654
pH	4.77	5.07	4.9765	0.01671	0.07471	0.006
Conductivity	1.91	3.62	2.9215	0.11350	0.50759	0.258
Stability%	14.81	59.26	35.5363	2.81192	12.57528	158.138
Density	0.85	0.95	0.8750	0.00526	0.02351	0.001
Colour	5.31	7.92	6.9260	0.17022	0.76123	0.579
Smell	3.90	5.78	5.1495	0.11012	0.49245	0.243
Acidity	2.50	3.33	2.9965	0.04605	0.20592	0.042
Watery	4.42	7.16	6.1140	0.15242	0.68166	0.465
Acceptability	4.46	6.39	5.1540	0.14086	0.62992	0.397

Table IV: A Correlation Matrix for all quality attributes.

	Viscosity (P1)	Viscosity Ratio (P2)	Mean particle size (P3)	pH (p4)	Conductivity (P5)	Stability% (P6)	Density(P7)	Colour (Q1)	Smell (Q2)	Acidity(Q3)	Watery(Q4)	Acceptability (Q5)
P1	1.00	.587	.305	-.363	-.434	.366	-.229	-.091	.261	.165	-.203	.131
P2	.587	1.00	.592	-.538	-.618	-.133	-.081	-.369	.284	-.152	-.197	.421
P3	.305	.592	1.00	-.632	-.166	.116	.081	-.614	.515	.168	-.444	.484
P4	-.363	-.538	-.632	1.00	.453	.208	.307	.593	-.535	-.239	.492	-.467
P5	-.434	-.618	-.166	.453	1.00	.384	.245	.096	-.014	.212	.048	.055
P6	.366	-.133	.116	.208	.384	1.00	-.128	-.016	.292	.419	-.191	.029
P7	-.229	-.081	.081	.307	.245	-.128	1.00	.241	-.293	-.317	.340	-.124
Q1	-.091	-.369	-.614	.593	.096	-.016	.241	1.00	-.734	-.222	.881	-.851
Q2	.261	.284	.515	-.535	-.014	.292	-.293	-.734	1.00	.625	-.884	.503
Q3	.165	-.152	.168	-.239	.212	.419	-.317	-.222	.625	1.00	-.549	-.079
Q4	-.203	-.197	-.444	.492	.048	-.191	.340	.881	-.884	-.549	1.00	-.609
Q5	.131	.421	.484	-.467	.055	.029	-.124	-.851	.503	-.079	-.609	1.00

The data fitness for building a quality structure model related to the physicochemical and sensory properties of the orange drinks examined was tested to verify the PCA procedure, as shown in Table V. The Kaiser-Meyer-Olkin (KMO) was somewhat inferior but above the lowest acceptable value (0.5). However, Bartlett's Test of Sphericity value was statistically significant at the 0.05 significance level (P-value < 0), indicating that the PCA procedure could be utilised to proceed with the data.

Table VI shows that each factor (quality attribute) has commonalities based on the principal component extraction method. Initial communalities always have equal values of 1 for the correlation analysis purpose, while extraction communalities have the variance estimates accounted for by the main components. Also, high values of extraction communalities were obtained, satisfactorily representing the quality attributes of orange drinks. Consequently, the commonalities extraction method was acceptable for this outcome.

The total variance explained by extracted main components shows the importance of the twelve quality attributes of orange drinks as the principal components. Therefore, Table VII represents the total variation calculated for the initial, extracted and rotated components after revising all the factors studied. The initial findings indicated that the first two principal components adequately characterise the twelve main quality attributes of the extracted solution. These two extracted components explained about 72% of the variation in the original twelve quality attributes. This means there was only a 28% information loss due to a significant dimension reduction when introducing those two principal components. Also, this outcome was confirmed using the rotation of extracted components. The cumulative percentage of the variation elucidated by the first two extracted components was retained compared to the initial solution with some change in variance, which was more uniformly scattered over the components.

In addition to the result above, it was clear that the eigenvalues of the first two components were more significant than one. It explained about 72 % of the total variation in the data collected. This outcome also confirmed that the first two principal components as the extracted solution could be satisfactory for the twelve quality attributes. In this case, the scree plot (Figure 5) was employed to graphically emphasise the same obtained outcome: the optimal number of principal components in terms of factors importance (two principal components). The plot illustrates the steep slope for the extraction solution of the first two components. The other components that contributed slightly to the extraction solution were on the shallow slope. Subsequently, the final significant descent was established between the first and second components to confirm the two principal components' choice as the extraction solution in the data collected.

Table V. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.585
Bartlett's Test of Sphericity	Approx. Chi-Square	52.038
	Df	15
	Sig.	0.000

Table VI. The Estimated Communalities for each Quality Attribute.

Communalities		
	Initial	Extraction
Viscosity	1.000	0.646
Mean particle size	1.000	0.592
Stability%	1.000	0.692
Colour	1.000	0.941
Smell	1.000	0.697
Acceptability	1.000	0.765

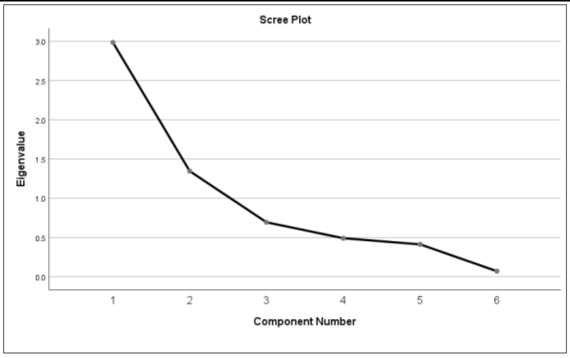

Figure 5. Scree Plot of Twelve Principal Components

Table VII: Total Variance Explained by Extracted Main Components.

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.986	49.767	49.767	2.986	49.767	49.767	2.848	47.461	47.461
2	1.346	22.436	72.202	1.346	22.436	72.202	1.484	24.741	72.202
3	0.694	11.562	83.764						
4	0.491	8.178	91.942						
5	0.413	6.877	98.819						
6	0.071	1.181	100						
Extraction Method: Principal Component Analysis.									

As mentioned, the extraction solution for the collected data was represented in the first two principal components. Therefore, Table VIII introduces the unrotated factor loadings for the main components. The expected pattern for the twelve quality attributes studied included high positive and negative factor loadings on each principal component. This pattern has the first two principal components as follows:

The first principal component was linked with high positive loadings of the smell and acceptability, followed by the mean particle size attribute and (simultaneously) high negative loadings of the colour attribute.

The second principal component positively and strongly correlated with the stability% and viscosity attributes. Thus, the two-factor extraction solution accurately represented the relationships in the data.

Table VIII. Component Matrix of Unrotated Factor Loadings

Component Matrix		
	Component	
	1	2
Colour	-0.914	0.325
Smell	0.830	.0.088
Acceptability	.0.818	-0.311
Mean particle size	0.769	0.016
Stability%	.0.269	0.732
Viscosity	0.254	0.792
Extraction Method: Principal Component Analysis		

According to the PCA procedure, the foremost step is identifying the number of critical quality attributes representing the overall quality of formulated orange drinks. This could be confirmed using Varimax rotation in the two-component matrix. Table IX shows that the factor loadings for each quality attribute of the orange drinks were calculated based on this rotation.

Table IX. Rotated Component Matrix

	Component	
	1	2
Colour (Q1)	**-0.969**	-0.045
Acceptability (Q5)	**.0.873**	-0.060
Smell (Q2)	**0.769**	0.326
Mean particle size (P3)	**0.731**	0.238
Stability% (P6)	0.013	**0.832**
Viscosity (P1)	.0.116	**0.790**
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. [a]		

The first principal component was positively associated with the orange drink's sensory and physicochemical properties (descending order): the overall acceptability, smell, and mean particle size. Conversely, it was highly negatively correlated with colour property (simultaneously). However, Particle size distribution can significantly affect sensory attributes, including appearance, taste, texture, and flavour [9,37,86]. The second principal component was positively linked with stability% and viscosity attributes (Figure 6). The texture and consistency of the orange beverage are improved by its viscosity and density values (i.e. smoothness and liquid quality). More practically, the orange drink can be classified as a non-Newtonian shear-thinning liquid, meaning its viscosity changes with temperature and pressure [9,37]. Consequently, each principal component's higher loading factors in determining the overall quality of the orange drinks were the colour, overall acceptability, smell, mean particle size (in terms of mouthfeel), physical stability percentage attribute, and apparent viscosity attribute.

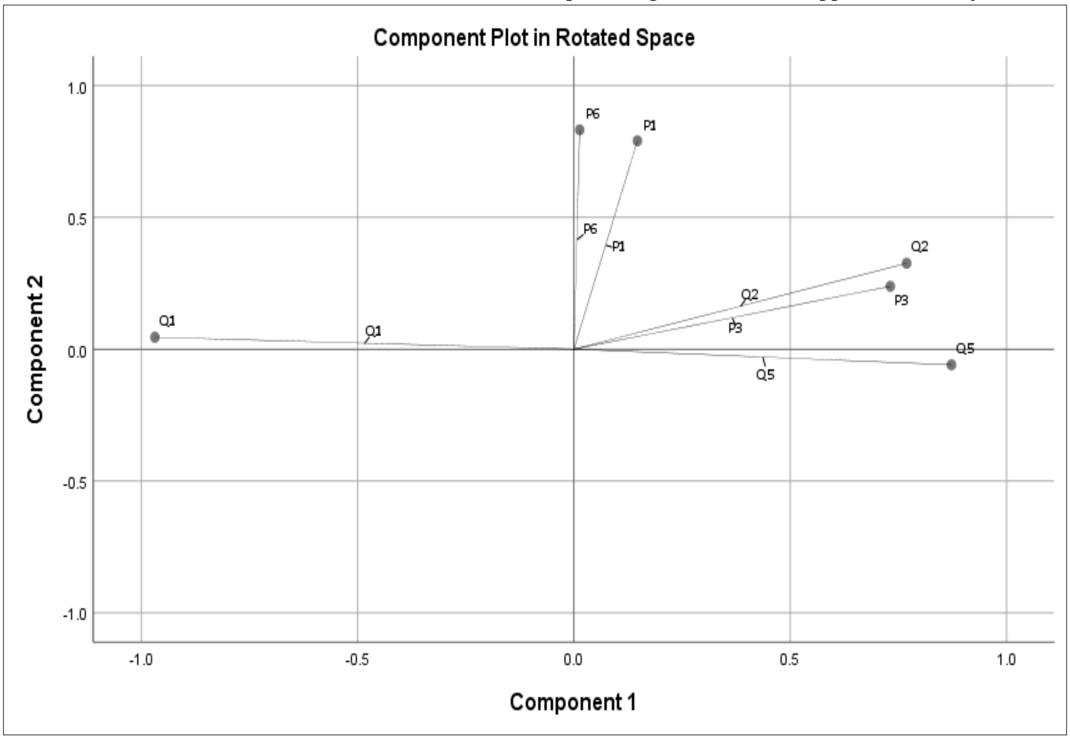

Figure 6. Components Biplot in Rotated Space

Subsequently, two important structural quality dimensions were found using the PCA procedure to involve all twelve quality attributes in a structural quality model: the first and second principal components. To adequately understand these quality factors of orange drinks, reasonable names were determined for each quality dimension (see Figure 5). The first significant quality dimension was named "*sensorial quality attributes*," including the colour, overall acceptability, smell attributes, and mean particle size (mouthfeel), which had high factor loading values. The second major quality dimension observed, "*physicochemical properties*," included physical stability and viscosity attributes. Their factor loading had the most significant values.

4.3. Interpretation of The Proposed Structural Quality Model

In this research "A Structural Quality Model for New Product Development to Enhance Resilience in Closed-Loop Formulated Food Supply Chains," various methods were employed to achieve the research objectives. PCA was used to reduce the dimensionality of the data and identify the most significant quality attributes by transforming correlated variables into a smaller number of uncorrelated variables called principal components. This helped in understanding the key factors that impact the quality of the formulated product. SEM, utilizing CFA, was employed to validate the structural model developed from these attributes, ensuring the relationships between observed and latent variables were accurately represented and assessed for convergent and discriminant validity. RSM based on CCD was implemented to explore the interactions between different ingredients and process parameters, optimizing the production process of the formulated product. Analytical methods were utilized to determine the physicochemical properties of the product, providing quantitative data on attributes such as viscosity, particle size, pH, and stability. This was complemented by QDA for sensory evaluation, where untrained consumer panels assessed the sensory properties of the product, helping to link consumer preferences with product characteristics.

Based on the results obtained, product design and development must be innovated by creating new innovative products to satisfy consumer requirements and different local market segments. Therefore, R&D departments in the manufacturing supply chains must continue designing new products to transfer product quality selected by consumers. In this regard, the designing and development methods must identify the most significant factors affecting the product or process quality in product, production, and consumer requirements to select the final formulated product based on many factors related to its characteristics. Thus, information and knowledge about the quality structure (physicochemical and sensory properties) may benefit the design and development process for R&D departments to focus on which dimensions are involved in the product development process during production. This is supported by reducing the number of main quality factors determining the formulated orange beverages to a lower number (i.e. two major components). Consequently, this reduces both costs and time in the R&D process.

As experienced in the market, formulated products come in diverse types for consumers, with several ingredients used in the product design or production stages at certain limits of concentrations due to health, safety, and manufacturing conditions. Thus, satisfying consumers at the early stages of product design and formulation, reformulation, or optimisation processes is essential. Therefore, a systematic methodology is vital for manufacturing the formulated products early in the product design and development process with acceptable quality limits. It is required to avoid uncertain factors and their possible risks. Such factors are included in the product design and manufacturing stages: delays, high cost and time, resource consumption and waste, safety and health hazards, flexibility, and other resilience elements. As a result, this method can be adjusted for various drinks and food items by tailoring the model to consider unique quality characteristics for each product type, like flavour, consistency, and nutritional value. This model can improve the productivity and performance of the new product development process across various food industries by pinpointing and ranking the most critical quality factors. Additionally, the model benefits the food industry as it helps make supply chain operations more efficient and reduce unpredictability, ultimately leading to more robust and sustainable supply chains.

The key findings of this research can be summarised as follows: (a) This study identified six independent quality factors influencing the overall quality of formulated orange beverages. These factors include colour, overall acceptability, smell, mean particle size (related to mouthfeel), physical stability percentage, and apparent viscosity attribute; (b) PCA was utilised to simplify the data by identifying the most crucial quality attributes. Subsequently, SEM was employed to validate the structural model derived from these attributes using CFA; (c) Measurement models were developed to assess the relationships between the six quality factors and their observed indicators, ensuring validity before evaluating and testing the structural model; (d)The results showed excellent model fit according to various indices, including CMIN/df, CFI, TLI, IFI, SRMR, and RMSEA; and (e) The proposed structural quality model can be used in different decentralised local markets, emphasising avoiding redesigning or remanufacturing at early stages.

According to the findings of the proposed model, the research proposes various areas for future work and possible enhancements. Expanding the research to encompass manufactured items from various sectors, like added value and consumer products, is a significant focus. This growth can offer a deeper insight into market and customer preferences. Moreover, the research could investigate fresh attributes, geographical extensions, and modifications to scalability to meet changing customer and application requirements. Another possible enhancement entails creating an expandable NPD business plan in SCS, focusing on re-distributed manufacturing and consumption. This model aims to boost production volumes, oversee new product lines, and broaden markets while maintaining product quality. These tactics may help companies manoeuvre through market changes, take advantage of new opportunities, and flourish in a constantly changing global environment.

5. Conclusions and Future Works

This research aimed to develop a structural quality model used to evaluate and reduce the number of quality attributes of food products. The proposed quality model consists of two principal components and determines the quality of formulated beverage products in the food and drinks industry.

A proposed methodology consisted of a combined PCA technique and multivariate statistical analysis to evaluate the quality attributes of the formulated product. Moreover, the developed model was confirmed by the CFA procedure using SEM. These attributes established the structural model: sensorial (acceptability, smell, and mean particle size (mouthfeel)) and physicochemical (viscosity and physical stability) properties. Therefore, this research used the orange beverage as a real-life case study to demonstrate a response to this challenge. In this case, the orange beverage's physicochemical and sensory properties were studied to develop a structural quality model that may be used as an empirical model in SCS R&D departments.

The results revealed a reduction in the factors affecting the quality of formulated beverage products compared to the two principal quality factors studied. This pattern involved diminishing the time and costs necessary for the NPD process in R&D methodologies. It expedited monitoring and controlling the formulated product quality in further product/process development to introduce newly formulated drinks products with the highest quality that meets consumer satisfaction and acceptability at decentralised locations. Thus, the development of this model benefits food supply chain integration and advanced manufacturing technology. As a practical implication, it is economically feasible, particularly for newly formulated product/process concepts linking to SCS. Additionally, by improving resource planning, alternative sourcing, logistic capacity planning, and logistic capabilities and lowering unforeseen fluctuations in both product supply and demand, SCS resilience can be boosted. This can be a crucial applied practice supported by top management to sustain competitive advantages in any manufacturing organisation and enhance the competencies of the decision-making process.

In order to improve the paper's relevance, it would be beneficial to extensively address potential difficulties and barriers that may arise when applying the suggested structural quality model in practical situations. Potential challenges may involve how well the model can adjust to ever-changing consumer needs, especially considering the ongoing shifts in consumer habits and desires. Furthermore, incorporating advanced technologies such as IoT, AI, and blockchain into the system could pose technical and operational obstacles, such as data merging, privacy worries, and the expensive nature of technological enhancements. Another challenge lies in the model's scalability, particularly in diverse geographic regions with different market dynamics and regulatory environments. Tackling these concerns would give a thorough grasp of the real-world consequences of implementing the model and advise businesses on handling these complications. However, as with most others, this research faces some potential limitations. The focus on designing and developing formulated consumer products was explicitly tailored to liquid-formulated food products, such as orange beverages. This narrowed focus may have omitted other types of formulated products, such as value-added and consumer products, potentially limiting the breadth of the study. Furthermore, there can be restrictions on the business model's ability to capture different viewpoints and target market dynamics due to its scalability.

In future studies, it would be advantageous to investigate different methodologies that can enhance the current quantitative methods, like mixed-methods research that integrates qualitative and quantitative data. Furthermore, broadening the research to encompass different product categories, such as value-added consumer goods and liquid food products, will offer a more comprehensive view of how well the model can be applied and how reliable it is. Researchers could explore the possibility of developing a business model that can grow in response to new features, market growth, and changes in customer demand. These suggestions would confirm the model's flexibility in various industries and boost its importance in a fast-changing worldwide market.

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References

[1] TronnebatI, I. and Jawab, F., “Green and Sustainable Supply Chain Management: A Comparative Literature Review”, Jordan Journal of Mechanical and Industrial Engineering, Vol.17, No. 1, 2023, pp.115-126.

[2] Chiu, S.W., “Production and Distribution Decisions for a Multi-product System with Component Commonality, Postponement Strategy and Quality Assurance Using a Two-machine Scheme”, Jordan Journal of Mechanical and Industrial Engineering, Vol.13, No. 2, 2019, pp.105-115.

[3] Rahimi, M. and Fazlollahtabar, H., “Optimization of a Closed Loop Green Supply Chain using Particle Swarm and Genetic Algorithms”, Jordan Journal of Mechanical and Industrial Engineering, Vol.11, No. 2., 2018, pp.105-112.

[4] Kuei, SC., Chen, MC., “Enablers of blockchain adoption on supply chain with dynamic capability perspectives with ISM-MICMAC analysis”, Annals of Operation Research,2023, pp.1-36. DOI: https://doi.org/10.1007/s10479-023-05684-w.

[5] Bafandegan Emroozi, V., Roozkhosh, P., Modares, A., & Roozkhosh, F., “Selecting Green Suppliers by Considering the Internet of Things and CMCDM Approach. Process Integration and Optimization for Sustainability, Vol.7, No. 5, 2023, pp. 1167–1189. DOI: https://doi.org/10.1007/s41660-023-00336-9.

[6] Bagheri, R., Zomorodi, P., & Rezaeian, A., “Identifying and ranking key technological capabilities in supply chain sustainability using ISM approach: case of food industry in Iran”; Environment, Development and Sustainability”, Vol.26, NO.4, 2023, pp. 9247-9284. DOI: https://doi.org/10.1007/s10668-023-03091-6.

[7] Rashed, C., et al., “Integrating Supply Chain Partners through Implementing Industry 4.0 Technologies to Enhance Competitiveness”, Jordan Journal of Mechanical and Industrial Engineering, Vol. 18, No.2, 2024, pp. 351- 363.

[8] Gupta, M., Kaur, H., & Singh, S., "Multi-echelon agri-food supply chain network design integrating operational and strategic objectives: A case of public distribution system in India", Annals of Operations Research, 2021, pp.1-58. DOI: https://doi.org/10.1007/s10479-021-04240-8.

[9] Jreissat, M., & Makatsoris, C., "Towards consumer driven food new product development: a closed-loop platform", International Journal of Computer Integrated Manufacturing, Vol. 35, No. 2, 2021, pp.183–202. DOI: https://doi.org/10.1080/0951192X.2021.1992652.

[10] Mishra, A., "Supply Chain Management in the Modern Era: Trends, Challenges, and Strategies", Indian Scientific Journal of Research in Engineering and Management, Vol. 7, NO. 8, 2023, pp.1-5. DOI: https://doi.org/10.55041/ijsrem25393.

[11] Serzhuk A.V., "Innovative technologies in supply chains", Intellectualization of logistics and Supply Chain Management, Vol. 22,2023, pp.40-45, https://doi.org/10.46783/smart-scm/2023-22-5.

[12] Holloway, S., "The Role of Supply Chain Flexibility in Adapting Marketing Strategies to Changing Consumer Preferences", Preprints, 2024, Available at: https://doi.org/10.20944/preprints202406.1759.v1.

[13] Earle, R. and Earle, M., "Fundamentals of Food Reaction Technology", Leatherhead International Limited, London, UK, 2003.

[14] Osteras, T., Murthy, D. and Rausand, M., "Product performance and specification in new product development", Journal of Engineering Design, Vol. 17, No. 2, 2006, pp.177-192.

[15] Miranda-Ackerman, M.A., Azzaro-Pantel, C. and Aguilar-Lasserre, A.A., "A green supply chain network design framework for the processed food industry: application to the orange juice agrofood cluster", Computers and Industrial Engineering, Vol. 109, 2017, pp.369-389.

[16] Govindan, K., "Sustainable consumption and production in the food supply chain: a conceptual framework", International Journal of Production Economics, Vol. 195, 2018, pp.419-431.

[17] Bryant, S.T., Straker, K. and Wrigley, C., "The rapid product design and development of a viable nanotechnology energy storage product", Journal of Cleaner Production, Vol. 244, 2020, pp.118725.

[18] Khodoomi, M., Seif, M. and Hanne, T., "Effects and challenges of the COVID-19 pandemic in supply chain management: a text analytics approach", Supply Chain Forum: An International Journal, 2023, pp.1-8. DOI: https://doi.org/10.1080/16258312.2023.2253523.

[19] Akter, S., Sultana, S., Gunasekaran, A., Bandara, R. J., & Miah, S. J., "Tackling the global challenges using data-driven innovations", Annals of Operations Research, Vol.333, No.2, 2024, pp. 517-532. DOI: https://doi.org/10.1007 /s10479-024-05875-z.

[20] Jain, V., Kumar, S., Soni, U. and Chandra, C., "Supply chain resilience: model development and empirical analysis", International Journal of Production Research, Vol. 55,2017, pp. 6779-6800. DOI: https://doi.org/10.1080/00207543.2017.1349947.

[21] Shirali, G.A., Shekari, M. and Angali, K.A., "Quantitative assessment of resilience safety culture using principal components analysis and numerical taxonomy: a case study in a petrochemical plant", Journal of Loss Prevention in the Process Industries, Vol. 40, 2016, pp.277-284, DOI: https://doi.org/10.1016/j.jlp. 2016.01.007.

[22] Raslan, R., Hassim, M.H., Chemmangattuvalappil, N.G., Ng, D.K.S. and Ten, J.Y., "Development of inherent safety and health index for formulated product design", Journal of Loss Prevention in the Process Industries, Vol. 66, 2020, pp.104209. DOI: https://doi.org/10.1016/j.jlp.2020.104209.

[23] Zavala-Alcívar, A., Verdecho, M.J. and Alfaro-Saiz, J.J., "A conceptual framework to manage resilience and increase sustainability in the supply chain", Sustainability, Vol.12, 2020, pp.1-3. DOI: https://doi.org/ 10.3390/SU12166300.

[24] Al-Ashhab MS, Aldosari N., "Modelling and Solving a Sustainable, Robust Multi-Period Supply Chain Network for Perishable Products", Indian Journal of Engineering, Vo. 19, NO. 51, 2022, pp.184-195.

[25] Pujawan, I. N., and Bah, A. U., "Supply chains under COVID-19 disruptions: literature review and research agenda", Supply Chain Forum: An International Journal, Vol.23, No.1, 2022, pp. 81–95.

[26] Waqas, U., Abd Rahman, A., Ismail, N. W., Kamal Basha, N., & Umair, S., "Influence of supply chain risk management and its mediating role on supply chain performance: perspectives from an agri-fresh produce", Annals of Operations Research, Vol. 324, NO.1, 2023, pp.1399–1427.DOI: https://doi.org/10.1007 /s10479-022-04702-7.

[27] Reddya, B. Chandra Mohana, et al., "Quota Allocation to Distributors of the Supply Chain under Distributors' Uncertainty and Demand Uncertainty by Using Fuzzy Goal Programming", Jordan Journal of Mechanical and Industrial Engineering, Vol. 2, No.4, 2008, pp. 215-226.

[28] Ocampo, L. and Clark, E., "A sustainable manufacturing strategy decision framework in the context of multi-criteria decision making," Jordan Journal of Mechanical and Industrial Engineering, Vol. 9, No. 3, 2015, pp.177-186.

[29] Cetindas, A., İ. Akben, I., Özcan, C., Kanusagı, I., and Öztürk, O., "The Effect of Supply Chain Agility on Firm Performance During COVID-19 Pandemic: The Mediating and Moderating Role of Demand Stability", Supply Chain Forum: An International Journal, Vol. 24, No. 3, 2003, pp. 307–318. DOI: https://doi.org/10.1080/16258312.2023.2167465.

[30] Shen, B., Zhang, J., Cheng, M., Guo, S., & He, R., "Supply chain integration in mass customization", Annals of Operations Research, 2023. DOI: https://doi.org/10.1007/s10479-023-05202-y.

[31] Shahsavani, I., Goli, A. & Hajiaghaei-Keshteli, M., "A circular economy approach to design a citrus supply chain network", Annal of Operations Research, 2024. DOI: https://doi.org/10.1007/ s10479-024-05829-5

[32] Balaji, M., et. al., "A Fuzzy Approach for Modeling and Design of Agile Supply Chains using Interpretive Structural Modeling", Jordan Journal of Mechanical and Industrial Engineering, Vol. 10, No. 1, 2016, pp. 67-74.

[33] Jreissat, M., and Jraisat, L. (2019), "Sustainable Dyads in Supply Chain Management: A Qualitative Perspective." Jordan Journal of Mechanical and Industrial Engineering Vol.13, No. 4., pp. 277-290.

[34] Jraisat, L., Jreissat, M., Sajjad, F., Batista, L., & Ghalia, T. (2022). No Actor is an Island: The Role of Partnerships in Sustainable Value Chains. Jordan Journal of Mechanical and Industrial Engineering, 16(2), 163-174.

[35] Srai, J.S., Harrington, T. S. and Tiwari, M. K., "Characteristics of redistributed manufacturing systems: a competitive study of emerging industry supply networks", International Journal of Production Research, Vol. 54, 2016, pp. 6936-6955.

[36] Kumar, S., Goyal A. and Singhal, A., "Manufacturing Flexibility and its Effect on System Performance", Jordan Journal of Mechanical and Industrial Engineering, Vol. 11, No. 2., 2017, pp.105-112.

[37] Jreissat, M., Isaev, S., Moreno, M. and Makatsoris, C., "Consumer driven new product development in future re-distributed models of sustainable production and consumption", Procedia CIRP, Vol. 63, 2017, pp.698-703.

[38] Liu, S., Papageorgiou, L.G. and Shah, N., "Optimal design of low-cost supply chain networks on the benefits of new product formulations", Computers and Industrial Engineering, Vol. 139, 2020. DOI: https://doi.org/10.1016/j.cie.2019.106189

[39] García, D., "Design of a Vendor Managed Inventory Model for Impulse Purchase Products in a Two-level Supply Chain", Jordan Journal of Mechanical and Industrial Engineering, Vol.14, No. 2, 2020, pp.257-270.

[40] Al-Ashhab MS, Al-Shami AAM, Mohamed MH. A., "Synergistic energy and production supply chain network design and planning optimization model considering multi-product and multi-periods", Indian Journal of Engineering, Vol.19, No. 52, 2022, pp.317-335.

[41] UK Cabinet Office, Food Matters: Towards a Strategy for the 21st Century, HM Stationary Office, London, UK, 2008. Available at: http://webarchive.nationalarchives.gov.uk/+/http:/www.cabinet office.gov.uk/ media/cabinetoffice/strategy/assets/food/food_analysis.pdf.

[42] Suwannaporn, P. and Speece, M., "Assessing new product development success factors in the Thai food industry", British Food Journal, Vol. 112 No. 4, 2010, pp.364-386.

[43] Aguilera, J., "Why food microstructure?", Journal of Food Engineering, Vol. 67, 2005, pp.3-11.

[44] Benner, M., Geerts, R.F.R, Linnemann, A.R., Jongen, W.M.F., Folstar, P. and Cnossen, H.J., "A chain information model for structured knowledge management: towards effective and efficient food product improvement", Trends in Food Science and Technology, Vol. 14, No.11, 2003, pp.469-477, DOI: https://doi.org/10.1016/S0924-2244(03)00154-7.

[45] Rong, A., Akkerman, R. and Grunow, M., "An optimisation approach for managing fresh food quality throughout the supply chain", International Journal of Production Economics, Vol. 131, No. 1,2011, pp.421-429.

[46] Tolonen, A., Haapasalo, H., Harkonen, J. and Verrollot, J., "Supply chain capability creation: the creation of the supply chain readiness for a new product during product development process", International Journal of Production Economics, Vol. 194, 2017, pp.237-245.

[47] Abdella, G.M., Kucukvara, M., Onat, N.C., Al-Yafay, H.M. and Bulakd, M.E., "Sustainability assessment and modeling based on supervised machine learning techniques: the case for food consumption", Journal of Cleaner Production, Vol. 251, 2020. DOI: https://doi.org/10.1016/j. jclepro.2019.119661.

[48] Stefansdottir, B. and Grunow, M., "Selecting new product designs and processing technologies under uncertainty: two-stage stochastic model and application to a food supply chain", International Journal of Production Economics, Vol. 201, 2018, pp.89-101.

[49] Birasnav, M. and Bienstock, J., "Supply chain integration, advanced manufacturing technology, and strategic leadership: an empirical study", Computers and Industrial Engineering, Vol. 130, 2019, pp.142-157, DOI: https://doi.org/10.1016/j.cie.2019.01.021.

[50] Apaiah, R., Hendrix, E., Meerdink, G. and Linnemann, A., "Qualitative methodology for efficient food chain design", Trends in Food Science and Technology, Vol. 16, 2005, pp.204-214.

[51] Nambiar, A. and Mahalik, N., "Trends in food packaging and manufacturing systems and technology", Trends in Food Science and Technology, Vol. 21 No. 3, 2010, pp.117-128.

[52] Zarei, M., Fakhrzad, M.B. and Jamali Paghaleh, M., "Food supply chain leanness using a developed QFD model", Journal of Food Engineering, Vol. 102, No. 1, 2011, pp.25-33.

[53] Ali, M.H. and Suleiman, N., "Sustainable food production: insights of Malaysian halal small and medium-sized enterprises", International Journal of Production Economics, Vol. 181, 2016, pp.303-314.

[54] Norton, I., Fryer, P. and Moore, S. (2006), "Product/process integration in food manufacture: engineering sustained health", AIChE Journal, Vol. 52 No. 5, pp.1632-1640.

[55] Trienekens, J. and Zuurbier, P., "Quality and safety standards in the food industry, developments and challenges", International Journal of Production Economics, Vol.113, No.1,2008, pp.107-122. DOI: https://doi.org/10.1016/j.ijpe.2007.02.050.

[56] Enyinda, C.I., Mbah, C.H.N. and Ogbuehi, A., "An empirical analysis of risk mitigation in the pharmaceutical industry supply chain: a developing-country perspective", Thunderbird International Business Review, Vol. 52, 2010, pp.45-54. DOI: https://doi.org/10.1002/tie.20309.

[57] Aigbogun, O., Ghazali, Z. and Razali, R., "Supply chain resilience and measurement dimensions: the case of halal pharmaceuticals in Malaysia", SHS Web of Conferences, Vol. 56,2018. DOI: https://doi.org/10.10 51/shsconf/20185605001.

[58] Jorge, V.F. and González, D., "Model to assess supply chain resilience", International Journal of Safety and Security Engineering,6, 2016, pp.282-292. DOI: https://doi.org/10.2495/SAFE-V6-N2-282-292.

[59] Ten, J.Y., Hassim, M.H., Chemmangattuvalappil, N. and Ng, D.K.S., "A novel chemical product design framework with the integration of safety and health aspects", Journal of Loss Prevention in the Process Industries, Vol. 40, 2016, pp.67-80. DOI: https://doi.org/10.1016/j.jlp.2015.11.027.

[60] Song, D., Yoon, E.S. and Jang, N., "A framework and method for the assessment of inherent safety to enhance sustainability in conceptual chemical process design", Journal of Loss Prevention in the Process Industries, Vol. 54, 2018, pp.10-17, DOI: https://doi.org/10.1016/j.jlp.2018.02.006.

[61] Su, Q., Moreno, M., Ganesh, S., Reklaitis, G.V. and Nagy, Z.K., "Resilience and risk analysis of fault-tolerant process control design in continuous pharmaceutical manufacturing", Journal of Loss Prevention in the Process Industries, Vol. 55, 2018, pp.411-422, DOI: https://doi.org/10.1016/j.jlp.2018.07. 015.

[62] Trienekens, J. and Omta, S., "Paradoxes in food chains and networks", in Trienekens, J.H., & Omta, S.W.F. Proceedings of the Fifth International Conference on Chain and Network Management in Agribusiness and the Food Industry, Noordwijk, The Netherlands, 2001.DOI: https://doi.org/10.3920/978-90-8686-507-9.

[63] Yan, T. and Azadegan, A., "Comparing inter-organisational new product development strategies: buy or ally; supply-chain or non-supply-chain partners?", International Journal of Production Economics, Vol. 183, 2017, pp.21-38.

[64] Buchholz, S., "Future manufacturing approaches in the chemical and pharmaceutical industry", Chemical Engineering and Processing: Process Intensification, Vol. 49, No. 10, 2010, pp.993-995.

[65] Schoenherr, T. and Wagner, S.M., "Supplier involvement in the fuzzy front end of new product development: an investigation of homophily, benevolence and market turbulence", International Journal of Production Economics, Vol. 180, 2016, pp.101-113.

[66] Enneking, U., Neumann, C. and Henneberg, S., "How important intrinsic and extrinsic product attributes affect purchase decision", Food Quality and Preference, Vol. 18, 2007, pp.133-138.

[67] Han, X. and Liu, X., "Equilibrium decisions for multi-firms considering consumer quality preference", International Journal of Production Economics, Vol. 227, 2020, pp.107688.

[68] Yao, X., Zhang, J., Li, Y. and Zhang, C., "Towards flexible RFID event-driven integrated manufacturing for make-to-order production", International Journal of Computer Integrated Manufacturing, Vol. 31, No. 3, 2018, pp.228-242.

[69] De Belie, N., Pedersen, D.K., Martens, M., Bro, R., Munck, L. and De Baerdemaeker, J., "The use of visible and near-infrared reflectance measurements to assess sensory changes in carrot texture and sweetness during heat treatment", Biosystems Engineering, Vol. 85, 2003, pp.213-225. DOI: https://www.doi.org/10.1016/ S1537-5110(03)00047-3.

[70] Geel, L., Kinnear, M. and Kock, H., “Relating consumer preferences to sensory attributes of instant coffee”, Food Quality and Preference, Vol. 16, 2005, pp.237-244.

[71] Schuchmann, H. and Schubert, H., “Product design in food industry using the example of emulsification”, Engineering and Life Sciences, Vol. 3, No. 2, 2003, pp.67-76.

[72] Gani, R., “Chemical product design: challenges and opportunities”, Computer and Chemical Engineering, Vol. 28, No. 12, 2004, pp.2441-2457.

[73] Teng, S.Y., How, B.S., Leong, W.D., Teoh, J.H., Cheah, A.C.S.C, Motavasel, Z. and Lam, H.L., “Principal component analysis-aided statistical process optimisation (PASPO) for process improvement in industrial refineries”, Journal of Cleaner Production, Vol. 225, 2019, pp.359-375, DOI: https://doi.org/10.1016/ j. jclepro.2019.03.272.

[74] Gani, R., “Computer-aided methods and tools for chemical product design”, Chemical Engineering Research and Design, Vol. 82, 2004, pp.1494-1504.

[75] Manzocco, L. and Nicoli, M., “Food design: from the methodological approach to the case study of low-calorie syrups”, Trends in Food Science and Technology, Vol. 13, 2002, pp.422-429.

[76] Conte, E., “Innovation in integrated chemical product-process design-development through a model-based system approach”, PhD thesis, Technical University of Denmark, 2010.

[77] Barbosa-Cánovas, G., Juliano, P. and Peleg, M., “Engineering properties of foods”, Food Engineering, Vol. 1, Encyclopedia of Life Support Systems (EOLSS), Oxford, UK,2006. Available at: http://www.eolss.net/ Sample-Chapters/C10/E5-10-01-00.pdf.

[78] Linnemann, A., Benner, M., Verkerk, R. and van Boekel, M.A., “Consumer-driven food product development”, Trends in Food Science and Technology, Vol. 17, 2006, pp.184-190.

[79] Luong, J.H. T., Bouvrette, P. and Male, K.B., “Developments and application of biosensors in food analysis”, Tibtech, Vol. 15 No. 9, 1997, pp.369– 377.

[80] Fellows, P., Food Processing Technology: Principles and Practice, 3rd ed, Woodhead Publishing Limited, Cambridge, UK; 2009.

[81] González-Martín, M.I., Severiano-Pérez, P. Revilla, I. Vivar-Quintana, A.M. Hernández-Hierro, J.M. González-Pérez, C., and Lobos-Ortega, I.A., “Prediction of sensory attributes of cheese by near-infrared spectroscopy”, Food Chemistry, Vol. 127, No. 1, 2011, pp.256-263. DOI: https://doi.org/10.1016/j. foodchem.2010.12.105.

[82] Favalli, S., Skov, T. and Byrne, D., “Sensory perception and understanding of food uniqueness: from the traditional to the novel”, Food Research International, Vol. 50, 2013, pp.176-188.

[83] Costell, E., Tarrega, A. and Bayarri, S., “Food acceptance: the role of consumer perception and attitudes”, Chemosensory Perception, Vol. 3, 2010, pp.42-50.

[84] Kraus, A. and Popek, S., “Structural model of fruit juice quality determining factors in product design and development”, British Food Journal, Vol. 115 No. 6, 2013, pp.865-875.

[85] Isaev, S., Jreissat, M., Wagner, C. and Makatsoris, C., “Linking human and machine: towards consumer-driven automated manufacturing”, 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2016. DOI: http://dx.doi.org/10.1109/ FUZZ-IEEE.2016.7737907.

[86] Piorkowski, D.T. and McClements, D.J., “Beverage emulsions: recent developments in formulation, production, and applications”, Food Hydrocolloids, Vol. 42, No. 1, 2014, pp.5-41.