Journal Pre-proof

Food quality 4.0: From traditional approaches to digitalized automated analysis

Abdo Hassoun, Sandeep Jagtap, Guillermo Garcia-Garcia, Hana Trollman, Mirian Pateiro, José M. Lorenzo, Monica Trif, Alexandru Rusu, Rana Muhammad Aadil, Vida Šimat, Janna Cropotova, José S. Câmara

Please cite this article as: Hassoun, A., Jagtap, S., Garcia-Garcia, G., Trollman, H., Pateiro, M., Lorenzo, José.M., Trif, M., Rusu, A., Aadil, R.M., Šimat, V., Cropotova, J., Câmara, José.S., Food quality 4.0: From traditional approaches to digitalized automated analysis, *Journal of Food Engineering* (2022), doi: https://doi.org/10.1016/j.jfoodeng.2022.111216.

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Food Quality 4.0: From traditional approaches to digitalized automated analysis

Abdo Hassoun [a,b,*], Sandeep Jagtap [c], Guillermo Garcia-Garcia [d], Hana Trollman [e], Mirian Pateiro [f], José M. Lorenzo [f,g], Monica Trif [h], Alexandru Rusu [i,j], Rana Muhammad Aadil [k], Vida Šimat [l], Janna Cropotova [m], José S. Câmara [n,o,*]

[a] Sustainable AgriFoodtech Innovation & Research (SAFIR), 62000 Arras, France; a.hassoun@saf-ir.com (A.H.)

[b] Syrian Academic Expertise (SAE), 27200 Gaziantep, Turkey

[c] Sustainable Manufacturing Systems Centre, School of Aerospace, Transport and Manufacturing, Cranfield University, Cranfield, MK43 0AL, United Kingdom; s.z.jagtap@cranfield.ac.uk (S.J.)

[d] Department of Agrifood System Economics, Institute of Agricultural and Fisheries Research and Training (IFAPA), Centre 'Camino de Purchil'. Camino de Purchil s/n. P.O. Box 2027, 18080 Granada, Spain; guillermo.garcia@juntadeandalucia.es (G.G-G.)

[e] School of Business, University of Leicester, Leicester LE2 1RQ, UK; ht203@leicester.ac.uk (H.T.)

[f] Centro Tecnológico de la Carne de Galicia, Parque Tecnológico de Galicia, Avd. Galicia n° 4, San CibraodasViñas, Ourense 32900, Spain;mirianpateiro@ceteca.net (M.P.); jmlorenzo@ceteca.net (J.M.L.)

[g] Universidade de Vigo, Área de Tecnoloxía dos Alimentos, Facultade de Ciencias, 32004 Ourense, Spain

[h] Food Research Department, Centre for InnovativeProcessEngineering (CENTIV) GmbH, 28857 Syke, Germany; monica_trif@hotmail.com (M.T.)

[i] Life Science Institute, University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca, 400372 Cluj-Napoca, Romania; rusu_alexandru@hotmail.com (A.R.)

[j] Faculty of Animal Science and Biotechnology, University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca, 400372 Cluj-Napoca, Romania

[k] National Institute of Food Science and Technology, University of Agriculture, Faisalabad 38000, Pakistan; muhammad.aadil@uaf.edu.pk (R.M.A.)

[l] University Department of Marine Studies, University of Split, R. Boškovića 37, HR-21000 Split, Croatia; vida@unist.hr (V.Š.)

[m] Norwegian University of Science and Technology, Department of Biological Sciences Ålesund, 6025 Ålesund, Norway; janna.cropotova@ntnu.no (J.C.)

31 [n] CQM – Centro de Química da Madeira, NPRG, Universidade da Madeira, Campus da Penteada, 9020-105

32   Funchal, Portugal; jsc@staff.uma.pt (J.S.C.)

33 [o] Departamento de Química, Faculdade de Ciências Exatas e Engenharia, Campus da Penteada,

34   Universidade da Madeira, 9020-105 Funchal, Portugal

35

36

37 ** Corresponding authors*

38 **Prof. José S. Câmara.** *E-mail address:*jsc@staff.uma.pt (J.S.C.). Will handle correspondence at all

39 stages of refereeing and publication.

40 Dr. Abdo Hassoun *E-mail address:* a.hassoun@saf-ir.com (A.H.).

41 Sustainable AgriFoodtech Innovation & Research (SAFIR), 62000 Arras, France.

42

ABSTRACT

Food quality has recently received considerable attention from governments, researchers, and consumers due to the increasing demand for healthier and more nutritious food products. Traditionally, food quality is determined using a range of destructive and time-consuming approaches with modest analytical performance, underscoring the urgent need to develop novel analytical techniques. The Fourth Industrial Revolution (called Industry 4.0) is progressing exponentially, driven by the advent of a range of digital technologies and other innovative technological advances. "Food Quality 4.0" is a new concept referring to the use of Industry 4.0 technologies in food analysis to achieve rapid, reliable, and objective assessment of food quality. In this review, we will first discuss the fundamentals and principles of Food Industry 4.0 technologies and their connections with the Food Quality 4.0 concept. Then, the most common techniques used to determine food quality will briefly be reviewed before highlighting the advancements made in analytical techniques to assess food quality in the era of Industry 4.0. Food Quality 4.0 is characterized by growing digitalization and automation of food analysis using the most advanced technologies in the food industry. Key aspects of Food Quality 4.0, including, among others, non-destructive fingerprinting techniques, omics technologies and bioinformatics tools, Artificial Intelligence and Big Data, have great potential to revolutionize food quality. Although most of these technologies are still under development, it is anticipated that future research will overcome current limitations for large-scale applications.

Keywords: Artificial Intelligence, automation, Big Data, digitalization, food, Industry 4.0, omics, quality, smart sensors, spectroscopy

1. Introduction

The modern food industry is a very competitive and dynamically developing environment, with increasing consumers' demands towards better food quality, safety, and shelf life, more product diversity and adoption of green/eco-friendly/sustainable production. Nevertheless, traditional processing technologies may affect sensory quality characteristics such as appearance, color, taste, and texture due to structural and conformational changes (e.g., lipid oxidation and protein denaturation) in food products. Therefore, to meet the constantly growing consumer demands for food products of high quality, food researchers and the food industry should constantly seek more advanced solutions and technologies, including innovative processing and analytical techniques (Echegary et al., 2022; García-Oliveira et al., 2020; Putnik et al., 2019).

Food quality refers to a range of attributes that are mainly related to sensory traits, shelf life, and freshness of food, but other properties associated with microbiological and technological parameters are also of utmost importance. During food processing and storage by using traditional and advanced non-thermal technologies, food's physicochemical and sensory quality is affected to some degree due to mechanical, electrical, or other physical damage to the microstructures of the cell wall and cell membrane. Currently, the assessment of food quality has been focused on conventional physicochemical methods, biological indicators, and sensory analysis, which are destructive, time-consuming, and laborious (Ren et al., 2022). These techniques are considered targeted methods and are often used to measure one specific aspect or a single well-described attribute of a given food (ElMasry & Nakauchi, 2016). However, non-targeted methods that simultaneously enable the acquisition of information about several parameters are more appropriate for measuring food quality. A remarkable innovation has recently been seen in the application and use of non-targeted detection methods to determine and monitor food quality (Hassoun, Siddiqui, et al., 2022; Özdoğan et al., 2021). Most non-targeted methods are well adopted with the principle

88   of non-destructive non-contact screening. The need for such techniques has been receiving even

89   more interest over the past two years due to the outbreak of the ongoing COVID-19 pandemic and

90   the increasing demand for less human contact with food (Khaled et al., 2021). Green foodomics

91   and   bioinformatics   technologies,   including   metabolomics   (e.g.,   chromatography–mass

92   spectrometry-based metabolomics, and NMR-based metabolomics), have gained much attention

93   (Balkir et al., 2021). Besides, image and spectroscopic techniques are becoming increasingly

94   interesting alternatives to traditional methods, enabling rapid online measurements (Mahanti et al.,

95   2022; McVey et al., 2021). These advanced analytical techniques have recently been empowered

96   by the advent of the Fourth Industrial Revolution (Industry 4.0) technologies.

97   Industry 4.0 has emerged due to the fusion of multidisciplinary fields, particularly the digital,

98   biological, and physical domains (Maynard, 2015). In the food industry, the ongoing Industry 4.0

99   era has been characterized by high interconnectivity and growing use of novel technologies,

100   especially digital innovations, e.g., Artificial Intelligence (AI), cloud computing and analytics, and

101   blockchain, and other emerging techniques, such as the Internet of Things (IoT), smart sensors,

102   autonomous robotics, and 3D food printing (Bouzembrak et al., 2019; Chowdhury et al., 2022;

103   Galvan et al., 2021; Hassoun, Aït-kaddour, et al., 2022; Hassoun, Siddiqui, et al., 2022). These

104   advanced technologies have accelerated digitalization and automation in almost all sectors,

105   including the food industry, enhancing rapid, online and in-site monitoring and intelligent food

106   quality control. According to the Scopus database, the number of publications and citations related

107   to digitalization or automation in food quality has increased tremendously in the last decade, and

108   it is still permanently increasing (**Fig. 1**).

109   <**Fig. 1** near here>

110 Quality 4.0 concept has been used in many fields, such as development and management,

111 organizational readiness, businesses, and leadership (Antony et al., 2021; Javaid et al., 2021; Sader

112 et al., 2021). However, there is a gap in literature, as up to date, no application has been reported

113 in the food industry or food-related fields.This work will introduce, for the first time,the "Food

114 Quality 4.0" concept referring to the use of Industry 4.0 technologies (e.g., AI, Big Data, smart

115 sensors, etc.) to determine food quality in the most efficient, rapid, and reliable manner. This

116 literature overview will show through specific examples how the application of the Food Quality

117 4.0 concept will contribute to ensuring high food quality, saving time and labor, and increasing the

118 efficiency of the food industry.

119 The main motivation of the study is to encourage more automation and digitalization in the food

120 industry. More concretely, this review paper aims to i) adopt the concept of Quality 4.0 in the food

121 industry; ii) define the main enablers of Food Quality 4.0; iii) promote wider applications of

122 Industry 4.0 technologies in the food industry; and iv) help to automate and digitalize quality

123 analysis in the food industry.

124 The organization of this manuscript is as follows: After the introduction, Section 2 gives a general

125 overview of Industry 4.0 technologies and introduces the Food Quality 4.0 concept. Section 3

126 presents the most common traditional methods as well as emerging techniques and approaches used

127 for the determination of food quality. Section 4 presents a short discussion, highlighting the main

128 theoretical and practical implications of Food Quality 4.0 and its relevance to policy makers. The

129 main conclusions, limitations, and future perspectives are briefly presented in Section 5.

130 This literature review was conducted with a methodology that focused on scientific articles

131 authored in the English language, published in peer-reviewed journals in the last ten years. Data

132 were obtained from Scopus with the following search criteria: Title, Abstract, Keyword; Food

133 Quality AND Digitalization OR Automation.

134

2. Food Industry 4.0 and "Food Quality 4.0" concept

136 Industry 4.0 is gaining momentum and supporting businesses to optimize their operations by

137 increasing automation and improving communication. It integrates recent developments in

138 information technology, such as robotics and automation, Big Data, simulation, system integration,

139 IoT, cybersecurity, the cloud, additive manufacturing, and augmented reality (Rüßmann, 2015), as

140 shown in **Fig. 2**. In addition, Industry 4.0 can help increase the efficiency of operations by

141 supporting the implementation of lean principles and methods, such as Just-in-time and Jidoka

142 (Rosin et al., 2019).

143 <**Fig. 2** near here>

144 Industry 4.0 principles are related to the three pillars of sustainability (i.e., environmental,

145 economic, and social domains). Ghobakhloo, (2020) analyzed such relationships and concluded

146 that Industry 4.0 is more connected to the economic domain of sustainability, mainly through

147 production efficiency and business model innovation. However, such principles can also pave the

148 way for improvements in the environmental and social domains. Bai et al.,(2020) ranked Industry

149 4.0 technologies based on their impact on sustainability performance and placed mobile

150 technologies first overall, while simulation ranked first in the food and beverage sector. Such

151 technologies contribute unequally to the economic, environmental, and social dimensions of

152 sustainability.

153 Although the implementation of Industry 4.0 technologies is generally expected to generate

154 industrial benefits, some of these technologies are still at a very early stage of adoption. As a result,

155 they do not offer clear benefits yet, especially in emerging economies (Dalenogare et al., 2018). In

156 this context, Raj et al.,(2020) analyzed the barriers to adopting Industry 4.0 technologies in the

157   manufacturing sector of developed and developing economies. They found that, although the lack

158   of a digital strategy alongside resource scarcity is the most significant barrier in both types of

159   economies, important differences exist between developed and developing countries. In developing

160   countries, improvements in standards and government regulation could facilitate the adoption of

161   Industry 4.0 technologies, whereas the focus should be on technological infrastructure in developed

162   countries. An important challenge to implementing Industry 4.0 more widely is the lack of expertise

163   and thus the need for a skilled workforce to operate such new systems (Sony & Naik, 2020).

164   The adoption of Industry 4.0 technologies varies significantly among European countries. The

165   Netherlands and Finland are leading the implementation thanks to their Industry 4.0 infrastructure

166   and Big Data maturity, while Hungary, Bulgaria, and Poland rank last (Castelo-Branco et al., 2019).

167   Sony & Naik, (2020) proposed factors from the following themes to assess Industry 4.0 readiness

168   for businesses (**Fig. 3**).

169   **<Fig. 3** near here>

170   Macroeconomic factors also influence the adoption of Industry 4.0, such as the structure of the

171   industrial sector, its role within each country's economy and differences in business models or

172   management styles (Castelo-Branco et al., 2019). Frank et al.,(2019) proposed a framework to

173   support the implementation of Industry 4.0 technologies in manufacturing businesses.

174   Food businesses are slowly embracing Industry 4.0 technologies, with sensors, simulations, AI-

175   based autonomous systems, additive manufacturing, cloud systems, and blockchain projected to

176   have the greatest impact in the sector. There are several examples of the application of such

177   technologies in various food-manufacturing applications, such as logistics (Jagtap, Bader, et al.,

178   2021); reduction of waste, energy and water use (Jagtap, Garcia-Garcia, et al., 2021); data

179   collection and monitoring (Konur et al., 2021a); and quality control (Garcia-Garcia et al., 2021).

180   Currently, Quality 4.0 is integrated with traditional quality practices rather than substituting them

181   (Sader et al., 2021). According to interviews with senior management professionals, the most

182   critical technologies for driving Quality 4.0 are predictive analytics, sensors and tracking, and

183   electronic feedback loops (Antony et al., 2021). Nevertheless, it is often difficult to transform

184   traditional quality-control processes into Quality 4.0 and obtain value from such changes.

185   Therefore, Escobar et al.,(2021) presented a problem-solving strategy based on seven steps

186   (namely, identify, accessorize, discover, learn, predict, redesign, and relearn) to increase the

187   likelihood of success in implementing Quality 4.0.

188   Quality control is key in the food sector, as it assures food products are safe for consumers and

189   have the required organoleptic properties. Quality 4.0 allows assessing the quality of food products

190   more accurately and in real-time (Ada et al., 2021), thus facilitating traceability (Khan et al., 2020),

191   which is a critical step toward more transparency in the food supply chains. There already exist

192   examples of the application of Quality 4.0 to optimize the quality-control process in food

193   businesses. Bhatia & Ahanger, (2021) presented an IoT-based framework to assess food-quality

194   parameters in restaurants and food outlets. Rejeb et al., (2020) analyzed the implementation of

195   blockchain technology for different applications, including quality assurance in the food supply

196   chain. Ping et al., (2018) reviewed the application of IoT technology in monitoring agricultural

197   product's quality and safety.

198   Furthermore, due to the high perishability of food products, smart packaging plays an important

199   role in food quality to extend the shelf life, improve quality, safety, and provide information about

200   food products. Technologies integrated into smart packaging include nano sensors, biosensors, and

201   gas sensors to measure the temperature and freshness of food products (Ben-Daya et al., 2020).

202   Implementation of Industry 4.0 technologies could create huge time and cost savings compared to

203   traditional analytical approaches. Although initial capital investment associated with innovative

204   technologies could be large, higher product quality, fewer errors, and reduced machine

205   downtimes,and other desirable features associated with smart technologies make the move from

206   traditional to Quality 4.0 system financially viable. For example, the application of blockchain will

207   not only solve problems of food safety and quality and improve transparency but also reduce costs

208   along the different stages and operations of food supply chain, such as transaction, quality, and

209   time costs, among other costs (Qian et al., 2022; Xu et al., 2020). Beside economic costs, a wider

210   implementation of digitalization, AI, and other Industry 4.0 elements has high potential to reduce

211   environmental costs by supporting the transition towards more sustainable food systems (Marvin

212   et al., 2022). Despite these advances, most of the innovative technologies are still under

213   development, and further research and testing is still required to accelerate the transitionfrom

214   laboratory to industrial-scale applications.

215   In conclusion, Industry 4.0 technologies show great potential for food businesses. Industry 4.0 may

216   optimize the quality-control process, key in the food sector, by increasing automation and

217   digitalization, and improving communication. The rest of the article reviews traditional methods

218   used to determine food quality and emerging techniques within Quality 4.0 that are expected to

219   contribute to the development of quality control in the food sector in the coming years.

220

221   **3. Findings**

222   **3.1. Traditional methods used for the determination of food quality**

223   Quality is defined through various characteristics, including nutritional value, physicochemical

224   properties, safety, sensory attributes, and shelf-life stability. Several standard and reference

225   methods have been used over the years to determine the quality and authenticity of food products,

226   mainly based on intrinsic attribute measurements (Bernués et al., 2003; Kutsanedzie et al., 2019).

227   Among them, physicochemical determinations (color, texture, water holding capacity) that are

228 related to product technological properties, sensory attributes (flavor, juiciness, tenderness) linked

229 to consumer acceptability, safety aspects including the presence of pathogenic and foodborne

230 microorganisms or toxic substances, and nutritional/health concerns (proximate composition, fatty

231 acid and amino acid composition) are included among these analytics (Lorenzo et al., 2022).

232 The most commonly used methods are supported by international organizations such as the AOAC

233 International, International Organization for Standardization (ISO), or the American Oil Chemists

234 Society (AOCS) (AOAC, 2019; ISO, 1981). The standards are intended to establish a quality

235 system, maintain product integrity, and satisfy customers. Others, such as *Codex Alimentarius* also

236 aim to protect consumers' health and guarantee and facilitate international food trade. In addition,

237 these methods allow the comparison of results, ensuring that the results are of quality.

238 There is no single standard method for proximate composition determination since the selection of

239 the method depends on the type of sample. This is clearly reflected in the case of lipids, where the

240 total content could be quantified by organic solvent extraction methods such as Soxhlet or Folch,

241 among others. In the case of protein, Kjeldahl and Dumas methods based on nitrogen measurements

242 are commonly used. In the case of total carbohydrate analysis, colorimetric and reducing sugar

243 methods are applied, while gravimetric procedures are the ones selected in the case of moisture and

244 ash. Moreover, spectroscopic methods are based on the absorption or emission of radiation in UV-

245 visible, and infrared frequency ranges are among the common instruments in many food

246 laboratories. In fact, these analyses can also be carried out using near-infrared reflectance

247 spectroscopy (NIRS), which allowsthe detection of product adulterations, predicting fat, protein

248 and water content quickly. Still, it has some limitations regarding instrument calibration and spectra

249 interpretation (Troy et al., 2016). In addition, the high absorbance of the NIRS signal by water

250 could disturb the results in products with high moisture content (Liu et al., 2015). In elemental

251 analysis, atomic emission spectroscopy (AAS), flame atomic emission spectroscopy (FAAS),

252 inductively coupled plasma-atomic emission spectrometry (ICP-OES) are among the

253 recommended techniques. In contrast, various chromatographic and mass spectrometry techniques

254 are used to identify these compounds in a more specific way (Di Stefano et al., 2012). **Fig. 4** shows

255 the traditional methods *vs.* emerging techniques for food quality determination.

256 <**Fig. 4** near here>

257 Regarding physicochemical parameters, color is one of the most important parameters that has a

258 huge impact on consumer acceptance, and is especially important in products, such as meat and

259 meat products, oils, or honey, among others (Brühl & Unbehend, 2021; Kuś et al., 2018;

260 Milovanovic et al., 2020; Tomasevic et al., 2019). It can be evaluated using visual or instrumental

261 methods. In the first case, color pattern cards or photographic scales are used. However, visual

262 evaluation is considered a subjective measure, since it is dependent on several factors, such as

263 testing conditions, lighting, color tones, training of assessors, and difficulty in finding matches

264 between standards and tested samples. In the case of instrumental measurements, the evaluation

265 based on the CIELAB system allows determining the exact color of the product in a three-

266 dimensional color sphere through the determination of three coordinates defined as L^*

267 (luminosity), a^* (redness-greenness), and b^* (yellow-blueness). Moreover, other parameters such

268 as chroma (C^*) and hue (h^*) can also be obtained from a^* and b^*.

269 Food texture is another determining characteristic in food products since it conditions food satiety,

270 the organoleptic experience of the consumer, and the overall acceptance of food products

271 (Guimarães et al., 2020). Sensory, instrumental (known as objective, physical or mechanical) and

272 indirect methods (collagen content, dry matter, among others) can be used to evaluate texture. The

273 main textural parameters evaluated in instrumental methods are hardness and cohesiveness,

274 although springiness, gumminess, and chewiness are also evaluated. These parameters are selected

275 depending on the product to be analyzed. The most common way to determine these parameters is

12

276 mechanical tests, such as the Warner-Bratzler test (WB) and texture profile analysis (TPA).

277 However, other parameters are more difficult to determine through instrumental methods. It is the

278 case of adhesiveness, creaminess, tenderness, and juiciness since these characteristics are more

279 linked to oral processing (Pascua et al., 2013). Therefore, they are usually evaluated through

280 sensory assessment. Consequently, many industries use both methodologies since they are

281 complementary and provide more reliable results. Along with these, the rheological properties of

282 foods are also determined to determine how the shape of the food changes in response to some

283 applied force. Other physicochemical parameters such as acidity or electrical conductivity could

284 complement the previous determinations, and in some cases, they would offer important data about

285 their quality.

286 In the case of microbiological analysis, there are several methodologies to determine the viability

287 of a product and the identification of microbial contaminants. However, cultivation continues to be

288 the most widely used method. It is the case of Total Viable Counts (TVC) determination,

289 considered as a standard tool (Hassoun, Gudjónsdóttir, et al., 2020). In addition to this, enzyme-

290 linked immune sorbent assay (ELISA) and polymerase chain reaction (PCR) are commonly used.

291 Other parameters can also be used as freshness indicators, along with these determinations. This is

292 the case of peroxide values (PV) and thiobarbituric acid reactive substances (TBARS), or protein

293 carbonyls and total volatile basic nitrogen (TVB-N), which are related to the stability of,

294 respectively, lipids and proteins to oxidation (Bekhit et al., 2021; Domínguez et al., 2019; Rubén

295 Domínguez et al., 2022).

296 The value of these analytics is unquestionable, but the results of these techniques must be correlated

297 with sensory analysis since the results obtained in the sensory characterization of a product are of

298 vital importance both in the development of new products and in their acceptance by the final

299 consumer (Ruiz-Capillas et al., 2021). Descriptive sensory analysis is the most usedmethod in

300 sensory characterization. The attributes are evaluated by a panel of highly trained panelists, making

301 the results obtained more objective and reliable. This, together with the fact that it is a flexible

302 method, has continued to be used over time (Purriños et al., 2022). The selected attributes usually

303 offer a large amount of information about the product whose intensity is evaluated within a

304 structured scale (Pateiro et al., 2022).

305 In summary, there are many methods conventionally used to determine food quality. However, it

306 is important to note that although they have good precision and reliability, in many cases, they

307 require several preliminary steps, are destructive, and are time-consuming (Hassoun et al., 2019),

308 highlighting the urgent need for more innovative and advanced analytical approaches.

309

310 **3.2. Emerging techniques and approaches**

311 *3.2.1. Non-destructive fingerprinting techniques*

312 As discussed before, conventional or traditional methods used to determine food quality have

313 several drawbacks, e.g., laborious and destructive nature, high cost, long process time, a limited

314 number of analytes, and low performance (El-Mesery et al., 2019; Khaled et al., 2021; Sarkar et

315 al., 2022; Valdés et al., 2021). These drawbacks can be faced by the Industry 4.0 vision or Quality

316 4.0 principles. Non-destructive, non-targeted fingerprinting methods (e.g., spectroscopic and

317 imaging techniques) can be more suitable for analyzing complex materials such as food products,

318 achieving rapid and cost-effective outcomes. Moreover, the need for such non-destructive methods

319 has become more evident in the last two years due to the outbreak of COVID-19 and the trend of

320 increased adoption of automation and AI in the food industry (Khaled et al., 2021).

321 This section will discuss a selection of the most common non-destructive fingerprinting techniques.

322 Spectroscopic techniques are based on the interaction between electromagnetic radiation and

323 matter at various wavelengths. Spectroscopic-based techniques can provide reliable information

324   about physical properties and the chemical composition of samples quickly and inexpensively, in

325   line with the core principles of Quality 4.0. A range of spectroscopic techniques, including, among

326   others, near-infrared (NIR) and mid-infrared (MIR) spectroscopy (Munawar et al., 2022; Pasquini,

327   2018; Su & Sun, 2019), fluorescence (Hassoun, 2021; Hassoun et al., 2019), and Raman

328   spectroscopy (Jiang et al., 2021; Lintvedt et al., 2022), has recently been gaining special attention

329   due to their desirable features such as high sensitivity and specificity and the possibility of being

330   applied on line during food production or processing for real-time data acquisition of intact

331   samples.

332   Spectroscopic methods have been widely used in many applications, ranging from detection of

333   adulteration and fraud (Hassoun, Måge, et al., 2020; Hassoun, Shumilina, et al., 2020; Rifna et al.,

334   2022; Silva et al., 2022; Zaukuu et al., 2022), determination of the chemical composition or specific

335   constituents (Xu et al., 2022), monitoring processing conditions, such as thermal and non-thermal

336   treatments (Abderrahmane Aït-Kaddour et al., 2021; Hassoun, Ojha, et al., 2020; Hassoun et al.,

337   2021; Hassoun, Heia, et al., 2020), to the determination of food quality and safety (Fan et al., 2022;

338   Hassoun & Karoui, 2017; Wang et al., 2018; Wu et al., 2021).

339   In recent years, tremendous progress has been made in miniaturized instrumentation, compact

340   spectral sensors and handheld systems (Giussani et al., 2022; Müller-Maatsch et al., 2021; Müller-

341   Maatsch & van Ruth, 2021; Rodriguez-Saona et al., 2020) has been made, driven by Industry 4.0

342   innovations and recent advancements. This trend has especially concerned NIR spectrometers that

343   have become available at a much smaller size and lower cost than traditional NIR benchtop

344   laboratory instruments (Beć et al., 2021; Giussani et al., 2022). Furthermore, the integration of AI,

345   deep learning, smart sensors, and other Industry 4.0 elements into spectroscopic systems has

346   enhanced the analytical performance of the proposed analysis systems. For example, in a recent

347 study, a portable system integrating NIR sensor, load sensor, and deep learning methods was

348 proposed for mixture powdery food evaluation (Zhou et al., 2022).

349 One of the most significant communication protocols for Industry 4.0 and IoT is Open Platform

350 Communications Unified Architecture (OPC-UA). OPC standardizes access to machines, devices,

351 and other systems in the industrial environment, allowing for identical and manufacturer-agnostic

352 data sharing (Ioana & Korodi, 2021). For example, a miniaturized spectrometer technology,

353 combined with AI was developed (called SmartSpectrometer) and used to predict sugar and acid

354 in grapes in the field. The open communication interface OPC-UA can be used to connect the

355 SmartSpectrometer modules on one side by ensuring interoperable data and information sharing

356 inside and on the other side between different Industry 4.0 automation levels. Production processes

357 can be optimized, quality can be improved, and resources can be saved by collecting and analyzing

358 spectroscopic measurement data and exchanging production-relevant information (Krause et al.,

359 2021).

360 Hyperspectral imaging (HSI) combines traditional spectroscopy and imaging and simultaneously

361 obtains spectral and spatial information. HSI has been most commonly used in Vis/NIR,

362 fluorescence, and Raman (Özdoğan et al., 2021; Qin et al., 2020). Three different sensing modes,

363 namely interactance, reflectance, and transmittance, are widely applied for various applications

364 (Hassoun, Heia, et al., 2020; Khaled et al., 2021; Ma et al., 2019). The technique can also be used

365 with microscopy systems (Pu et al., 2019). Data created by HSI has a three-dimensional structure;

366 x, y, λ (called hypercube), with two spatial dimensions (x rows, y columns) and one spectral

367 dimension (a range of wavelengths).A detailed overview of HSI principles, different configurations

368 and settings, and various hardware and software can be found in other review papers (Caporaso et

369 al., 2018; Fu & Chen, 2019; Ma et al., 2019; Wang et al., 2021).

370 HSI was first used in remote-sensing applications, but the range of applications has recently

371 become very large, including food quality (Caporaso et al., 2018; Pu et al., 2019; Saha &

372 Manickavasagan, 2021). HSI can be used to evaluate external quality attributes and internal quality

373 parameters (Hassoun et al., 2021; Khaled et al., 2021; Ma et al., 2019; Wang et al., 2021). HSI is

374 most used in sensory and freshness assessment (Özdoğan et al., 2021), authentication (Qin et al.,

375 2020), and determination of the quality of different food categories such as egg (Yao et al., 2022),

376 meat (Fu & Chen, 2019), and fruits and vegetables (Lu et al., 2017). Recent research has shown

377 that most of the quality indicators (discussed in Section 3), such as TVB-N, TBARS, TPA, and

378 color, can be predicted from HSI data. Some relevant examples of recent applications of HSI in the

379 field of food quality control can be found in **Table 1**. This table shows that HSI has been widely

380 used in various food products, mostly of animal origin, and the Vis/NIR range (especially 400-

381 1000 nm) has been the most used mode.

382 *<Table 1 near here>*

383 Compared to other techniques, HSI has many desirable features that meet Industry 4.0

384 requirements. The technique is characterized by high speed, accuracy, automation, and real-time

385 monitoring and could be suitable for automated quality evaluation and safety inspection of large

386 sample sets. Although most investigations have been conducted at the laboratory level, HSI has

387 great potential for industrial applications (El-Mesery et al., 2019; Lu et al., 2017; Özdoğan et al.,

388 2021). One of the main limitations of HSI remains the huge amount of obtained data that should

389 be processed in real-time. However, with the rapid developments in technology (especially the

390 recent advancements of Industry 4.0 and the combination of HSI with Big Data and cloud-

391 computing technologies), the development of new algorithm models for optimal wavelength

392 selection and implementation of multispectral imaging have enabled higher computing efficiency

393 and enhanced the entire system performance, demonstrating the feasibility of using HSI to evaluate

394   numerous properties of various food products (Khaled et al., 2021; Ma et al., 2019; Özdoğan et al.,

395   2021).

396   Besides spectroscopic and imaging techniques, a wide range of analytical methods have been

397   developed in recent years. These include acoustic and ultrasound sensing (Caladcad et al., 2020;

398   Lei & Sun, 2019), machine vision system and computer vision (El-Mesery et al., 2019; Kakani et

399   al., 2020; Saberioon et al., 2017), bioelectrical impedance analysis (Fan et al., 2021; Huh et al.,

400   2021), wireless chemical sensors and biosensors, such as radio-frequency identification (RFID)

401   (Karuppuswami et al., 2020; Kassal et al., 2018), electronic nose and electronic tongue (Di Rosa

402   et al., 2017), just to mention a few. However, most of these techniques are still under development

403   and require more research to meet industrial needs.

404   *3.2.2. Omics and bioinformatics technologies*

405   Generally, foods represent very complex and diverse mixtures consisting of naturally occurring

406   compounds including primary and secondary metabolites such as lipids, proteins, carbohydrates,

407   amino acids, fatty acids, phytochemicals, colorants, aromas, preservatives, among others, in

408   addition to several other exogenous compounds, which pose enormous analytical challenges. The

409   assessment of these metabolites and the monitoring of food quality and food safety imply the use

410   of robust, sensitive, cost-effective, and efficient analytical methodologies.

411   Currently, the most common high-throughput analytical techniques that are well accepted and

412   taken as gold standards for food quality assessment and safety monitoring are liquid (LC) or gas

413   chromatography (GC), usually coupled to mass spectrometry (MS), nuclear magnetic resonance

414   (NMR) spectroscopy, and capillary electrophoresis (CE) (**Fig. 5**).

415   <**Fig. 5** near here>

416   In addition to those molecular analysis methods, other methodological approaches of biological

417   origin, such as ELISA and PCR, are also used extensively in food analysis (Tramuta et al., 2022;

418   Xu et al., 2022). Although these methods have been in use for a long time (hence their introduction

419   in Section 3), recent advances and developments in terms of instrumentation and techniques have

420   revolutionized many aspects of analytical chemistry. Coupled with machine learning, these

421   techniques are a promising way of modelling food-human interaction. In recent years,

422   bioinformatics technologies have been gaining popularity, especially with the increased need for

423   enhanced computational capabilities to process huge biological data, enabling effective monitoring

424   of food quality (Jeevanandam et al., 2022). Omics is a sub domain of "foodomics" that studies food

425   and nutrition domains through the application and integration of advanced omics technologies,

426   such as proteomics (proteins), metabolomics (metabolites), and genomics (detection of genes),

427   among others (Balkir et al., 2021; Carrera et al., 2020; Picone et al., 2022).

428   One of the most powerful analytical techniques that has played a vital role in food safety and quality

429   issues, in addition to food authenticity and labeling accuracy as a useful tool to prevent food fraud

430   and adulteration, is liquid chromatography with ultraviolet (LC-UV) detection or coupled to mass

431   spectrometry (LC-MS) (Malik et al., 2010; Núñez et al., 2005).The characterization of food

432   products based on LC analytical methodologies has been reported in several works, providing a

433   large amount of information, such as the confirmation and quantification of thousands of

434   compounds in one chromatographic run (Núñez et al., 2005). For example, native Colombian fruits

435   and their by-products were characterized by Loizzo et al., (2019) by determining their

436   hypoglycemic potential antioxidant activity and phenolic profile. The presence of chlorogenic acid

437   as a dominant compound in Solanaceae samples was revealed by ultra-high performance liquid

438   chromatography-high resolution mass spectrometry (UHPLC-HRMS) with an Orbitrap mass

439   analyzer. Izquierdo-Llopart & Saurina, (2019) established the polyphenolic profiles (280, 310 and

440 370 nm) of sparkling wines by LC-UV/Vis and principal component analysis (PCA). Figueira et

441 al., (2021) established the fingerprint of the free low molecular weight phenolic composition and

442 bioactivity of *Vacciniumpadifolium* Sm. fruits by LC-MSMS, while Aguiar et al., (2020) reported

443 the chemical fingerprint of free polyphenols and antioxidant activity in dietary fruits and vegetables

444 using a non-targeted approach based on QuEChERS-ultrasound assisted extraction combined with

445 UHPLC-FLR.

446 In a recent study, Reyrolle et al.,(2022) selected ion flow tube mass spectrometry (SIFT-MS)was

447 developed to detect and quantify volatile organic compounds emitted by ewe cheeses, illustrating

448 producer's typicality and process control and the impact of the animals' diet on the final product

449 without any previous separation step. Other applications of chromatography and spectrometry

450 techniques for the analysis of food metabolites and metabolomics research have been recently

451 reviewed (Emwas et al., 2021; Pedrosa et al., 2021).

452 NMR is a non-destructive analytical method based on the magnetic properties of several atomic

453 nuclei, in which the spin nuclear magnetization of a sample that contains NMR active nuclei and

454 is located inside a strong field NMR magnet, is excited by radio-frequency pulses generating a

455 signal, which during its relaxation back to equilibrium, is recorded and Fourier transformed to

456 provide the NMR spectrum. The most common nuclei studied in food analysis are

457 hydrogen, deuterium, carbon, and phosphorus (Higashi et al., 2020; Pedrosa et al., 2021;

458 Wieczorek et al., 2021). NMR is well suited to omics approach. It is a versatile and accurate

459 quantitative technique that can be applied to samples of all states of matter for quality control,

460 production monitoring/improvement, sensory evaluation, and food authentication. However, its

461 sensitivity is relatively low compared to other high-throughput technologies. High-resolution solid

462 state (Munson et al., 2022) and liquid state NMR (Dubrow et al., 2022) are the most common NMR

463 techniques applied to food to obtain a frequency domain spectrum.

464   CE is another emerging technique that has generated great interest in the analyses of many

465   compounds due to its high separation efficiency, extremely small sample and reagent requirements,

466   and rapid analysis. Recently, Valdés et al., (2022) presented a detailed overview of the main

467   applications (e.g., detection and analyzing carbohydrates, amino acids, biogenic amines,

468   heterocyclic amines, lipids, proteins and peptides, vitamins, among others)of CE methods in food

469   analysis and foodomics. Another review paper provided an overview of the application of MS,

470   NMR, CE and other metabolomics approaches for the characterization of meat and the exploration

471   of biomarkers in the production system (Muroya et al., 2020).

472   Despite the numerous obvious advantages and the important capabilities and possibilities offered

473   by the application of omics and bioinformatics, these main characteristics of the Quality 4.0 era are

474   not without challenges. The main obstacles are the complexity and variety of data generated from

475   different bioinformatics tools, expensive instrumentation, and lack of skilled operators needed for

476   method development (Valdés et al., 2021, 2022).

477

478   *3.3. Artificial Intelligence (AI) and Big Data*

479   Industry 4.0 includes innovative technologies, such as Big Data and AI. Deep learning and Big

480   Data are among the most important topics of Industry 4.0 (Zeba et al., 2021). These technologies

481   exist within smart ecosystems: humans, machines, and devices interact for efficient product

482   manufacturing. These technologies improve food manufacturing efficiency and consistency and

483   reduce operational costs. They may be implemented to adapt existing machinery to a new way of

484   operating instead of expensive replacement (Konur et al., 2021b). Integrating Big Data and AI into

485   traditional food science can create new recipes alongside intelligent recommendations, track and

486   trace food for improved food quality, and analyze food taste preferences.

487   *3.3.1. Agriculture*

488   Agri-food supply chains are the source of quality raw materials transformed into quality

489   manufactured foods. In response to consumer demand for affordable and higher quality food, agri-

490   food supply chains deploy AI and Big Data to guide decision-making to improve food product

491   quality through traceability, reduced waste and improved productivity. For example, AI can assess

492   plants and fruits at various harvest stages and post-harvest stages to detect effects such as decay

493   and mold (Stasenko et al., 2021). There are, however, challenges to the digitalization of agri-food

494   supply chains such as low inter-operability of different data sets, silo mentality, low willingness to

495   share data and a significant skills gap (Serazetdinova et al., 2019).

496   Our ability to assess crop quality at scale in the fields has recently improved due to remote sensing

497   and AI, which integrate Big Data into predictive and prescriptive management tools to address

498   agricultural and human nutrition challenges (Jung et al., 2021). AI has great potential to support

499   the transition to sustainable food systems, impacting the entire value chain from farmers to

500   consumers (Marvin et al., 2022). AI may be combined with ontological models to improve the

501   product quality of vertical farms, supporting autonomous data-driven decisions (Abbasi et al.,

502   2021). Further optimization and decision-making support may be derived from digital twins that

503   rely on AI and Big Data for even greater insights (Nasirahmadi & Hensel, 2022).

504   *3.3.2. Traceability*

505   Food traceability is an important means of ensuring food quality that addresses trust issues between

506   consumers and the market. RFID technology and Big Data may be used to obtain information about

507   the food production process (Zheng et al., 2021). Processed food is particularly challenging due to

508   the variety of raw materials, batch mixing and resource transformation. In the context of processed

509   food, AI may be used to optimize batch mixing and Big Data can support quality forecasting (Qian

510   et al., 2022). It is predicted that blockchain technology will be integrated with AI and Big Data,

511   supporting a new level of supply chain traceability.

512 *3.3.3. Food processing quality*

513 With respect to food processing, AI-based 3D food printing can produce high quality, customized

514 products for individuals based on appropriateness judgments and standards for food ingredients

515 supported by Big Data values of various food groups (Yoo & Park, 2021). Furthermore, new food

516 product development can look to "computational pharmaceutics" (Wang et al., 2021) for

517 inspiration on integrating Big Data, AI and multi-scale modelling techniques for pre-formulation

518 studies and predicting nutritional effects. Recently, AI used in conjunction with simple sound

519 vibrations traversing the food product has demonstrated the ability to verify high-quality products

520 with no additives and organic food products (Iymen et al., 2020).

521 *3.3.4. Sensors and food quality*

522 Determining the quality of a food product may also be aided by sensor data combined with AI and

523 Big Data. Non-destructive spectroscopic, acoustic, ultrasound and artificial sensing techniques

524 have immense food quality testing applications. The application of computer vision and learning

525 methods to improve the food industry is termed "computer vision and AI-driven food industry"

526 (Kakani et al., 2020).

527 Biogenic amines are important biomarkers for monitoring food quality that benefit from AI's

528 application; this application may be a new way to monitor the freshness of meat (Tan et al., 2022).

529 Non-destructive inspection based on X-ray CT scans has been used with a deep neural network to

530 indicate suboptimal storage conditions of pear fruits. In addition, the technique can be used to

531 detect internal disorders, such as internal browning and cavity formation, which are often invisible

532 from the outside (Van De Looverbosch et al., 2021).

533 Nonthermal technologies such as high-power ultrasound, pulsed electric fields, high voltage

534 electrical discharge, high-pressure processing, UV-LED, pulsed light, e-beam, and advanced

535 thermal food processing techniques including microwave processing, ohmic heating, and high-

536 pressure homogenization may all benefit from the implementation of smart sensors combined with

537 AI and Big Data (Jambrak et al., 2021). AI may support food quality analysis using food images

538 (from smartphones) to estimate their nutrient content (Ma et al., 2022). In addition, AI human-like

539 sensors exist for vision, hearing, smell, taste and touch (Zhao et al., 2020), which may complement

540 and eventually replace human sensory tests of food quality.

541 Big Data and AI afford opportunities for multi-parameter sensing that mimics the sense of taste,

542 overcoming the limitations of salty, sweet, sour, bitter and glutamate sensing by using electronic

543 taste chip systems that can act as fingerprints of health and wellness (Christodoulides et al., 2019).

544 In addition, E-sensing and nanoscale-sensing devices may be combined with AI for food quality

545 control (Galvan et al., 2021)(Galvan et al., 2021)[20](Galvan et al., 2021). However, although there

546 is significant literature investigating food product quality with computer vision algorithms, there

547 is a lack of commercial exploitation (Meenu et al., 2021).

548 *3.3.5. Food safety and food quality*

549 The globalization of food production makes ensuring food quality more difficult. Therefore, a

550 reliable digital ecosystem of food quality management requires a balanced strategy for the

551 integration of Big Data, AI and blockchain for the end-to-end monitoring of food quality and safety

552 and improvement of quality management and traceability of food products at all stages –

553 production, circulation and consumption (Savina et al., 2020).

554 *3.3.6. Food supply chain and cold chain*

555 The main challenge of Sustainable Development Goal 12, "Responsible Consumption and

556 Production", is the reduction of food losses along production and supply chains. Improving food

557 product quality is particularly important for fresh food products to avoid waste and losses. Big Data

558 and AI may bring new solutions to mitigate the perishability nature of fresh food products (Vernier

559 et al., 2021).

24

560 Constructing a traceable system for cold chain logistics would help brand image and increase

561 consumer trust by delivering safe and higher-quality food products (Wang et al., 2020;

562 Zhuangzhuang, 2020). Traditional systems may be slow to adjust the fresh food storage

563 temperature. Temperature control algorithms using AI and Big Data may be used to adjust the

564 temperature environment so that food is consistently at the optimal storage temperature (Guan et

565 al., 2021).

566 *3.3.7. Packaging*

567 Food quality depends on food packaging methods and materials. AI and Big Data can be used to

568 assess a range of environmental factors near food manufacturing sites and impacts within a variable

569 food packaging value chain for better decision-making on packaging materials aligned with the

570 Sustainable Development Goals (Sand, 2020). Furthermore, recent advances in nanotechnology

571 have enabled the development of small devices and nano-sized sensors that could be incorporated

572 in food packaging or even in smartphones giving consumers the ability to assess the quality and

573 investigate the properties of their own food easily (Saadat et al., 2022).

574

575 **4. Discussion and implications**

576 Our literature overview revealed that some of the recently developed technologies can be

577 considered promising options in food quality assessment. Specifically, the use of spectroscopic

578 techniques (NIR, MIR, fluorescence, and Raman spectroscopy) in addition to HSI has received

579 much attention in the determination of food quality. For example, the HSI technique generates both

580 spectral and spatial data, showing promising results for various classification purposes and

581 prediction of many traditional quality parameters (e.g., TVB-N, TBARS, TPA, and color). Imaging

582 and spectroscopic techniques have demonstrated considerable capacity to detect food fraud and

583 determine chemical composition, food quality and safety parameters, as well as monitor particular

584   quality parameters during production, processing, or storage of food. Most of these techniques are

585   non-destructive, relatively low-cost, and generate data that contains maximum information,

586   providing a "fingerprint" of the investigated food product. Other analytical methods, such as mass

587   spectrometry and chromatographic methods are powerful tools to determine freshness parameters,

588   safety, authenticity, traceability, and overall quality of foods, but they often require large

589   equipment and experienced laboratory personnel.

590   Recently, "omics" has emerged as a sub-domain of "foodomics" that refers to the study of

591   proteomics (proteins), metabolomics (metabolites), among others, through the application of

592   advanced platforms of electrophoresis, molecular approaches, nuclear magnetic resonance

593   spectroscopy, and others (Creydt & Fischer, 2018; Singh et al., 2021). More recently, food quality

594   monitoring through bioinformatics, Big Data, machine learning, AI, IoT, and smart sensors has

595   received huge considerations (Bouzembrak et al., 2019; Goyal et al., 2022; Jagatheesaperumal et

596   al., 2021; Jeevanandam et al., 2022; Kumar et al., 2021; Marvin et al., 2022; Mavani et al., 2021).

597   These Industry 4.0 elements have revolutionary features (e.g., allowing obtaining robust data,

598   appropriate for real-time measurements, and saving time and costs), making them most suitable for

599   the future Food Quality 4.0 era.

600   Our findings highlight the importance of AI and Big Data as a crucial pillar of Food Quality 4.0

601   era. The use of these digital quality enablers in agriculture, traceability, food processing quality,

602   packaging, and other stages along the supply and cold chains has been demonstrated through

603   concrete examples. However, the findings from our review shows that research studies dealing

604   with the application of Industry 4.0 technologies in the food industry are limited. This is likely due

605   to the silo mentality and the conservative nature of the food industry compared to other industrial

606   sectors (Chapman et al., 2022; Hassoun et al., 2020), in addition to other limitations that will be

607   discussed in the next section.

608   The introduction of Quality 4.0 concept into the food industry could have several theoretical and

609   practical implications. Theoretically, the incorporation of Food Quality 4.0 will address the gap

610   highlighted in the literature regarding the scarce of research investigating application of Industry

611   4.0 technologies in the food industry. Food Quality 4.0 opens up promising avenues for future

612   research in several digitalization and automation technologies. Although, most of the topics

613   discussed in this work were previously reviewed in more detail in other publications, to the best of

614   our knowledge, this manuscript is the first to raise awareness of the importance of multidisciplinary

615   approaches and simultaneously considering a wide range of emerging technologies that address the

616   key principle of Industry 4.0, namely the convergence between various areas of science, especially

617   physical, biological, and digital disciplines.

618   In practice, this research can be used as a basis for understanding the different challenges and

619   opportunities offered by adopting Quality 4.0 in the food industry. More adoption of Quality 4.0

620   enablers will ensure best quality management practices of raw materials and final food products

621   during production, processing and commercialization. Close collaboration and cooperation

622   between different actors is needed to optimally implement and fully exploit and harness the

623   potential of Industry 4.0 in food quality.

624

5. Conclusions, limitations, and future research perspectives

626   The main objective of this work is to discuss the concept of Food Quality 4.0, highlighting the

627   potential of emerging analytical methods and smart technologies, in the context of the Fourth

628   Industrial Revolution (Industry 4.0), for enhancing food quality. Industry 4.0 technologies have a

629   significant role to play in sustainable social, environmental, and economic development. Although

630   the Quality 4.0 concept has been used in many other disciplines, such as manufacturing

631   development, management, and related fields (Antony et al., 2021; Javaid et al., 2021; Sader et al.,

632   2021), up to date, an obvious gap in literature can be noticed since no application has been reported

633   in the food industry. This review paper provides an up-to-date source of information about the

634   latest developments and advances in food quality assessment methods by introducing, for the first

635   time, the concept of "Food Quality 4.0" in food-related applications.

636   The results of this review may help policy makers to move toward fostering and supporting

637   transdisciplinary collaboration to embrace more technological innovations. Long-term policy-

638   making strategies are needed to facilitate the adoption of the Industry 4.0 paradigm, and

639   consequently accelerate the implementation of Food Quality 4.0. The results of our literature

640   review show that, despite the increased research attention directed to the importance of Industry

641   4.0 technologies, there are a lot of uncertainties regarding the wider adoption of these technologies

642   in the food industry. There is still a lack of serious awareness related to Industry 4.0 features within

643   the food quality context. However, the interest for Industry 4.0 among managers and policy-makers

644   has increased significantly in recent years. Managers and policy-makers should set out on a journey

645   towards Food Quality 4.0 by identifying the measures (such as incentives, roadmaps, and

646   consultancy services) that could facilitate the implementation of Industry 4.0 technologies in small

647   and medium-sized enterprises (Matt et al., 2020). The role of new generation (young managers and

648   leaders) having an open-mindset should be strengthen and prioritized in decision-making process

649   to overcome the limitation of silo mentality, which is a well-known character of food industry.

650   The efficiency of food quality and safety assessment methods, as well as food processing

651   technologies come into question with every food crisis and pandemic outbreak, seriously

652   undermining consumer confidence. The role policy makers is particularly important during crises,

653   such as the coronavirus pandemic. For this reason, it is ever more important, during and in the wake

654   of the COVID-19 pandemic, to develop rapid and non-destructive techniques to measure food

655   quality efficiently and objectively.

656   Food quality is traditionally determined using intrinsic attributes, such as physical, chemical,

657   microbial, and technical (processing) parameters, through the application of numerous methods

658   that are time-consuming, laborious, and destructive. In contrast, Industry 4.0 technologies have

659   strong prospects for overcoming these limitations. By combining the physical, digital, and

660   biological worlds, Industry 4.0 has recently begun to automate and digitalize many food production

661   and consumption sectors thanks to the implementation of AI, Big Data analytics, IoT, smart

662   sensors, robotics, and other digital and innovative technologies along the whole food value chain.

663   Industry 4.0 innovations and technologies can be employed to enable Food Quality 4.0, improving

664   efficiency, rapidity, and reliability of food assessment techniques.

665

666   A successful transition from the traditional to Food Quality 4.0 system implies some prerequisites

667   and challenges that need to be addressed. While Food Quality 4.0 offers various advantages

668   concerning automation and digitalization in food quality analysis, it faces various obstacles. The

669   techniques need to be more affordable, adequate in size, and efficient in industrial environments.

670   High cost, lack of adaptability to the existing industrial environment, and lack of technical skills

671   are among the most challenging bottlenecks hindering the wider application of these technologies.

672   Inadequate infrastructure facilities, especially in developing countries are also a critical limitation

673   that needs to be addressed.

674   Besides the challenges related to implementation of Quality 4.0 concept and obstacles facing the

675   application of emerging technologies, some limitations linked to the approach used in this review

676   paper can be highlighted. Although most relevant studies (mainly extracted from Scopus) have

677   been reported, more systematic reviews that consider bibliometric approaches to visualize results

678   should be conducted in the future. A larger source of data, including, in addition to Scopus, Web

679   of Science, Google Scholar, and other online databases (e.g., IEEE Explore, SAGE Publications,

680   and MDPI, among others) should be considered.

681   However, in line with the ongoing efforts put into the development of technical innovations and

682   digital solutions, it is expected that the limitations of these emerging techniques will be overcome.

683   More research is needed to better understand the contribution of Industry 4.0 technologies to Food

684   Quality 4.0. Optimal quality monitoring (once achieved by implementing Food Quality 4.0

685   principles) means smart quality controls and high-quality assurance of food products, reduced food

686   waste and loss, and decreased use of resources and energy, thus enhancing the transition towards

687   more sustainable food systems.

688

701   **Conflicts of Interest:** The authors declare no conflict of interest.

31

702 **Author Contributions**

703 Abdo Hassoun: Conceptualization, methodology, writing—original draft preparation, revision,

704 editing. Sandeep Jagtap, Guillermo Garcia-Garcia, Hana Trollman, Mirian Pateiro, José M.

705 Lorenzo, Monica Trif, Alexandru Rusu, Rana Muhammad Aadil, Vida Šimat, Janna Cropotova:

706 writing—original draft preparation, revision. José S. Câmara: writing—original draft preparation,

707 revision, supervision, Review & Editing.All authors have read and agreed to the published version

708 of the manuscript."

709

References

Abbasi, R., Martinez, P., & Ahmad, R. (2021). An ontology model to represent aquaponics 4.0 system's knowledge. *Information Processing in Agriculture*, *in press.* https://doi.org/10.1016/J.INPA.2021.12.001

Ada, N., Kazancoglu, Y., Sezer, M. D., Ede-Senturk, C., Ozer, I., & Ram, M. (2021). Analyzing barriers of circular food supply chains and proposing Industry 4.0 solutions. *Sustainability*, *13*(12), 6812. https://doi.org/10.3390/SU13126812

Aguiar, J., Gonçalves, J. L., Alves, V. L., & Câmara, J. S. (2020). Chemical fingerprint of free polyphenols and antioxidant activity in dietary fruits and vegetables using a non-targeted approach based on QuEChERS ultrasound-assisted extraction combined with UHPLC-PDA. *Antioxidants* , *9*(4), 305. https://doi.org/10.3390/ANTIOX9040305

Aheto, J. H., Huang, X., Tian, X., Lv, R., Dai, C., Bonah, E., & Chang, X. (2020). Evaluation of lipid oxidation and volatile compounds of traditional dry-cured pork belly: The hyperspectral imaging and multi-gas-sensory approaches. *Journal of Food Process Engineering*, *43*(1), 1–10. https://doi.org/10.1111/jfpe.13092

Aït-Kaddour, A., Hassoun, A., Bord, C., Schmidt-Filgueras, R., Biancolillo, A., Di Donato, F., Temiz, H. T., & Cozzolino, D. (2021). Application of spectroscopic techniques to evaluate heat treatments in milk and dairy products: An overview of the last decade. *Food and Bioprocess Technology,* 14, 781–803. https://doi.org/10.1007/s11947-021-02607-0

Al-Sarayreh, M., Reis, M. M., Yan, W. Q., & Klette, R. (2020). Potential of deep learning and snapshot hyperspectral imaging for classification of species in meat. *Food Control*, *117*, 107332. https://doi.org/10.1016/J.FOODCONT.2020.107332

Antony, J., McDermott, O., & Sony, M. (2021). Quality 4.0 conceptualisation and theoretical understanding: a global exploratory qualitative study. *TQM Journal*, *in press*. https://doi.org/10.1108/TQM-07-2021-0215

735   AOAC. Official methods of analysis 21st ed. Gaithersburg, MD: Association of Official Analytical

736   Chemists International; 2019.

737   Baek, I., Lee, H., Cho, B. kwan, Mo, C., Chan, D. E., & Kim, M. S. (2021). Shortwave infrared hyperspectral

738   imaging system coupled with multivariable method for TVB-N measurement in pork. *Food Control*,

739   *124*, 107854. https://doi.org/10.1016/j.foodcont.2020.107854

740   Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability

741   perspective.   *International   Journal   of   Production   Economics*,   *229*,   107776.

742   https://doi.org/10.1016/J.IJPE.2020.107776

743   Balkir, P., Kemahlioglu, K., & Yucel, U. (2021). Foodomics: A new approach in food quality and safety.

744   *Trends in Food Science and Technology*, *108*, 49–57. https://doi.org/10.1016/j.tifs.2020.11.028

745   Ballesteros-Vivas, D., Socas-Rodríguez, B., Mendiola, J. A., Ibáñez, E., & Cifuentes, A. (2021). Green food

746   analysis: Current trends and perspectives. *Current Opinion in Green and Sustainable Chemistry*, *31*,

747   100522. https://doi.org/10.1016/J.COGSC.2021.100522

748   Beć, K. B., Grabska, J., & Huck, C. W. (2021). Principles and applications of miniaturized near-infrared

749   (NIR)   spectrometers.   *Chemistry   –   A   European   Journal*,   *27*(5),   1514–1532.

750   https://doi.org/10.1002/CHEM.202002838

751   Bekhit, A. E. D. A., Holman, B. W. B., Giteru, S. G., & Hopkins, D. L. (2021). Total volatile basic nitrogen

752   (TVB-N) and its role in meat spoilage: A review. *Trends in Food Science and Technology*, *109*, 280–

753   302. https://doi.org/10.1016/j.tifs.2021.01.006

754   Ben-Daya, M., Hassini, E., Bahroun, Z., & Banimfreg, B. H. (2020). The role of internet of things in food

755   supply chain quality management: A review.   *Quality Management Journal* , *28*(1), 17–40.

756   https://doi.org/10.1080/10686967.2020.1838978

757   Bernués, A., Olaizola, A., & Corcoran, K. (2003). Extrinsic attributes of red meat as indicators of quality in

758   Europe: An application for market segmentation. *Food Quality and Preference*, *14*(4), 265–276.

759   https://doi.org/10.1016/S0950-3293(02)00085-X

760   Bhatia, M., & Ahanger, T. A. (2021). Intelligent decision-making in Smart Food Industry: Quality

761   perspective.   *Pervasive   and   Mobile   Computing*,   *72*,   101304.

762   https://doi.org/10.1016/J.PMCJ.2020.101304

763   Bouzembrak, Y., Klüche, M., Gavai, A., & Marvin, H. J. P. (2019). Internet of Things in food safety:

764   Literature review and a bibliometric analysis. *Trends in Food Science & Technology*, *94*, 54–64.

765   https://doi.org/10.1016/J.TIFS.2019.11.002

766   Brühl, L., & Unbehend, G. (2021). Precise color communication by determination of the color of vegetable

767   oils and fats in the CIELAB 1976 (L * a * b *) color space. *European Journal of Lipid Science and*

768   *Technology*, *123*(7), 2000329. https://doi.org/10.1002/ejlt.202000329

769   Caladcad, J. A., Cabahug, S., Catamco, M. R., Villaceran, P. E., Cosgafa, L., Cabizares, K. N., Hermosilla,

770   M., & Piedad, E. J. (2020). Determining Philippine coconut maturity level using machine learning

771   algorithms based on acoustic signal. *Computers and Electronics in Agriculture*, *172*, 105327.

772   https://doi.org/10.1016/J.COMPAG.2020.105327

773   Caporaso, N., Whitworth, M. B., & Fisk, I. D. (2018). Near-Infrared spectroscopy and hyperspectral

774   imaging for non-destructive quality assessment of cereal grains. *Applied Spectroscopy Reviews*, *4928*,

775   1–21. https://doi.org/10.1080/05704928.2018.1425214

776   Carrera, M., Piñeiro, C., & Martinez, I. (2020). Proteomic strategies to evaluate the impact of farming

777   conditions   on   food   quality   and   safety   in   aquaculture   products.   *Foods* ,   *9*(8),   1050.

778   https://doi.org/10.3390/FOODS9081050

779   Castelo-Branco, I., Cruz-Jesus, F., & Oliveira, T. (2019). Assessing Industry 4.0 readiness in manufacturing:

780   Evidence   for   the   European   Union.   *Computers   in   Industry*,   *107*,   22–32.

781   https://doi.org/10.1016/J.COMPIND.2019.01.007

782   Chapman, J., Power, A., Netzel, M. E., Sultanbawa, Y., Smyth, H. E., Truong, V. K., & Cozzolino, D.

783   (2022). Challenges and opportunities of the fourth revolution: a brief insight into the future of food.

784   *Critical   Reviews   in   Food   Science   and   Nutrition*,   *62*   (10),   2845-2853.

785   https://doi.org/10.1080/10408398.2020.1863328

786   Chaudhry, M. M. A., Hasan, M. M., Erkinbaev, C., Paliwal, J., Suman, S., & Rodas-Gonzalez, A. (2021).

787   Bison muscle discrimination and color stability prediction using near-infrared hyperspectral imaging.

788   *Biosystems Engineering*, *209*, 1–13. https://doi.org/10.1016/J.BIOSYSTEMSENG.2021.06.010

789   Chen, Z., Wang, Q., Zhang, H., & Nie, P. (2021). Hyperspectral imaging (HSI) technology for the non-

790   destructive freshness assessment of pearl gentian grouper under different storage conditions. *Sensors*

791   *(Switzerland)*, *21*(2), 1–13. https://doi.org/10.3390/s21020583

792   Cheng, J. H., Sun, D. W., & Wei, Q. (2017). Enhancing visible and near-infrared hyperspectral imaging

793   prediction of TVB-N level for fish fillet freshness evaluation by filtering optimal variables. *Food*

794   *Analytical Methods*, *10*(6), 1888–1898. https://doi.org/10.1007/s12161-016-0742-9

795   Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong,

796   L. (2022). Unlocking the value of artificial intelligence in human resource management through AI

797   capability framework. *Human Resource Management Review*, 100899.

798   https://doi.org/10.1016/J.HRMR.2022.100899

799   Christodoulides, N., McRae, M. P., Simmons, G. W., Modak, S. S., & McDevitt, J. T. (2019). Sensors that

800   learn: The evolution from taste fingerprints to patterns of early disease detection. *Micromachines* ,

801   *10*(4), 251. https://doi.org/10.3390/MI10040251

802   Claire Koelsch Sand. (2020). *Beta, XR, AI, and big data advance food packaging*. Retrieved March 22,

803   2022, from https://www.ift.org/news-and-publications/food-technology-

804   magazine/issues/2020/september/columns/packaging-beta-xr-ai-and-big-data-advance-food-

805   packaging

806   Creydt, M., & Fischer, M. (2018). Omics approaches for food authentication. *Electrophoresis*, *39*(13),

807   1569–1581. https://doi.org/10.1002/elps.201800004

808   Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry

809   4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*,

810   383–394. https://doi.org/10.1016/J.IJPE.2018.08.019

811   Di Rosa, A. R., Leone, F., Cheli, F., & Chiofalo, V. (2017). Fusion of electronic nose, electronic tongue and

812   computer vision for animal source food authentication and quality assessment – A review. *Journal of*

813   *Food Engineering*, *210*, 62–75. https://doi.org/10.1016/j.jfoodeng.2017.04.024

814   Di Stefano, V., Avellone, G., Bongiorno, D., Cunsolo, V., Muccilli, V., Sforza, S., Dossena, A., Drahos, L.,

815   & Vékey, K. (2012). Applications of liquid chromatography-mass spectrometry for food analysis.

816   *Journal of Chromatography A,* 1259, 74–85. https://doi.org/10.1016/j.chroma.2012.04.023

817   Dixit, Y., Al-Sarayreh, M., Craigie, C. R., & Reis, M. M. (2021). A global calibration model for prediction

818   of intramuscular fat and pH in red meat using hyperspectral imaging. *Meat Science*, *181*, 108405.

819   https://doi.org/10.1016/J.MEATSCI.2020.108405

820   Domínguez, R., Pateiro, M., Gagaoua, M., Barba, F. J., Zhang, W., & Lorenzo, J. M. (2019). A

821   comprehensive review on lipid oxidation in meat and meat products. *Antioxidants*, *8*(10), 429.

822   https://doi.org/10.3390/ANTIOX8100429

823   Domínguez, Rubén, Pateiro, M., Munekata, P. E. S., Zhang, W., Garcia-Oliveira, P., Carpena, M., Prieto,

824   M. A., Bohrer, B., & Lorenzo, J. M. (2022). Protein oxidation in muscle foods: A comprehensive

825   review. *Antioxidants*, *11*(1), 60. https://doi.org/10.3390/ANTIOX11010060

826   Dubrow, G. A., Tello, E., Schwartz, E., Forero, D. P., & Peterson, D. G. (2022). Identification of non-

827   volatile compounds that impact consumer liking of strawberry preserves: Untargeted LC–MS analysis.

828   *Food Chemistry*, *378*, 132042. https://doi.org/10.1016/J.FOODCHEM.2022.132042

829   Echegary, N., Yegin, S., Kumar, M., Hassoun, A., Bastianello Campagnol, P. C., & Lorenzo, J. M. (2022).

830   Application of oligosaccharides in meat processing and preservation. *Critical Reviews in Food Science*

831   *and Nutrition*, *in press*. https://doi.org/10.1080/10408398.2022.2081963

832   El-Mesery, H. S., Mao, H., & Abomohra, A. E. F. (2019). Applications of non-destructive technologies for

833   agricultural and food products quality inspection. *Sensors*, *19*(4), 846.

834   https://doi.org/10.3390/S19040846

835   ElMasry, G., & Nakauchi, S. (2016). Image analysis operations applied to hyperspectral images for non-

836   invasive sensing of food quality – A comprehensive review. *Biosystems Engineering*, *142*, 53–82.

837   https://doi.org/10.1016/J.BIOSYSTEMSENG.2015.11.009

838   Emwas, A. H. M., Al-Rifai, N., Szczepski, K., Alsuhaymi, S., Rayyan, S., Almahasheer, H., Jaremko, M.,

839   Brennan, L., & Lachowicz, J. I. (2021). You are what you eat: Application of metabolomics

840   approaches   to   advance   nutrition   research.   *Foods*,   *10*(6),   1249.

841   https://doi.org/10.3390/FOODS10061249

842   Escobar, C. A., McGovern, M. E., & Morales-Menendez, R. (2021). Quality 4.0: A review of big data

843   challenges   in   manufacturing.   *Journal   of   Intelligent   Manufacturing*,   *32*(8),   2319–2334.

844   https://doi.org/10.1007/S10845-021-01765-4/FIGURES/14

845   Fan, K.-J. ;, Su, W.-H., Fan, K.-J., & Su, W.-H. (2022). Applications of fluorescence spectroscopy, RGB-

846   and MultiSpectral imaging for quality determinations of white meat: A review. *Biosensors* , *12*(2), 76.

847   https://doi.org/10.3390/BIOS12020076

848   Fan, X., Lin, X., Wu, C., Zhang, N., Cheng, Q., Qi, H., Konno, K., & Dong, X. (2021). Estimating freshness

849   of ice storage rainbow trout using bioelectrical impedance analysis. *Food Science and Nutrition*, *9*(1),

850   154–163. https://doi.org/10.1002/fsn3.1974

851   Feng, C. H., Makino, Y., Yoshimura, M., Thuyet, D. Q., & García-Martín, J. F. (2018). Hyperspectral

852   imaging in tandem with R statistics and image processing for detection and visualization of pH in

853   Japanese big sausages under different storage conditions. *Journal of Food Science*, *83*(2), 358–366.

854   https://doi.org/10.1111/1750-3841.14024

855   Figueira, J. A., Porto-Figueira, P., Pereira, J. A. M., & Câmara, J. S. (2021). Free low-molecular weight

856   phenolics composition and bioactivity of *Vaccinium padifolium* Sm fruits. *Food Research*

857   *International*, *148*, 110580. https://doi.org/10.1016/J.FOODRES.2021.110580

858   Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns

859   in   manufacturing   companies.   *International   Journal   of   Production   Economics*,   *210*,   15–26.

860   https://doi.org/10.1016/J.IJPE.2019.01.004

861   Fu, X., & Chen, J. (2019). A review of hyperspectral imaging for chicken meat safety and quality evaluation:

862   Application, hardware, and software. *Comprehensive Reviews in Food Science and Food Safety*, *18*(2),

863   535–547. https://doi.org/10.1111/1541-4337.12428

864   Galvan, D., Aquino, A., Effting, L., Mantovani, A. C. G., Bona, E., & Conte-Junior, C. A. (2021). E-sensing

865   and nanoscale-sensing devices associated with data processing algorithms applied to food quality

866   control: A systematic review. *Critical Reviews in Food Science and Nutrition*, *in press.*

867   https://doi.org/10.1080/10408398.2021.1903384

868   Garcia-Garcia, G., Coulthard, G., Jagtap, S., Afy-Shararah, M., Patsavellas, J., & Salonitis, K. (2021).

869   Business process re-engineering to digitalise quality control checks for reducing physical waste and

870   resource use in a food company. *Sustainability*, *13*(22), 12341. https://doi.org/10.3390/SU132212341

871   García-Oliveira, P., Fraga-Corral, M., Pereira, A. G., Prieto, M. A., & Simal-Gandara, J. (2020). Solutions

872   for the sustainability of the food production and consumption system. *Critical Reviews in Food Science*

873   *and Nutrition*, *62* (7), 1765-1781. https://doi.org/10.1080/10408398.2020.1847028

874   Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner*

875   *Production*, *252*, 119869. https://doi.org/10.1016/J.JCLEPRO.2019.119869

876   Giussani, B., Gorla, G., & Riu, J. (2022). Analytical chemistry strategies in the use of miniaturised NIR

877   Instruments: An   overview.   *Critical   Reviews   in   Analytical   Chemistry*,   *in   press*.

878   https://doi.org/10.1080/10408347.2022.2047607

879   Goyal, K., Kumar, P., & Verma, K. (2022). Food adulteration detection using artificial intelligence: A

880   systematic   review.   *Archives   of   Computational   Methods   in   Engineering*,   *29*(1),   397–426.

881   https://doi.org/10.1007/s11831-021-09600-y

882   Guan, X., Huang, L., & Zhang, L. (2021). Design of comprehensive service system for fresh food E-

883   commerce under the Background of "rural Revitalization." *Journal of Physics: Conference Series*,

884   *1757*(1). https://doi.org/10.1088/1742-6596/1757/1/012141

885 Guimarães, J. T., Balthazar, C. F., Silva, R., Rocha, R. S., Graça, J. S., Esmerino, E. A., Silva, M. C.,

886   Sant'Ana, A. S., Duarte, M. C. K. H., Freitas, M. Q., & Cruz, A. G. (2020). Impact of probiotics and

887   prebiotics on food texture. *Current Opinion in Food Science*, 33, 38–44.

888   https://doi.org/10.1016/j.cofs.2019.12.002

889 Guo, W., Li, X., & Xie, T. (2021). Method and system for nondestructive detection of freshness in Penaeus

890   vannamei based on hyperspectral technology. *Aquaculture*, *538*, 736512.

891   https://doi.org/10.1016/j.aquaculture.2021.736512

892 Hassoun, A., & Karoui, R. (2017). Quality evaluation of fish and other seafood by traditional and

893   nondestructive instrumental methods: Advantages and limitations. *Critical Reviews in Food Science

894   and Nutrition*, *57*(9). https://doi.org/10.1080/10408398.2015.1047926

895 Hassoun, A., Ojha, S., Tiwari, B., Rustad, T., Nilsen, H., Heia, K., Cozzolino, D., El-Din Bekhit, A.,

896   Biancolillo, A., & Wold, J. P. (2020). Monitoring thermal and non-thermal treatments during

897   processing of muscle foods: A comprehensive review of recent technological advances. *Applied

898   Sciences (Switzerland)*, *10*(19). https://doi.org/10.3390/app10196802

899 Hassoun, Abdo. (2021). Exploring the potential of fluorescence spectroscopy for the discrimination between

900   fresh and frozen-thawed muscle foods. *Photochem*, *1*(2), 247–263.

901   https://doi.org/10.3390/PHOTOCHEM1020015

902 Hassoun, Abdo, Aït-kaddour, A., Abu-mahfouz, A. M., Rathod, N. B., Bader, F., Barba, F. J., Cropotova,

903   J., Galanakis, C. M., Jambrak, A. R., Lorenzo, M., Måge, I., Ozogul, F., Regenstein, J., Rathod, B.,

904   Bader, F., Barba, F. J., Biancolillo, A., Cropotova, J., Galanakis, M., … Regenstein, J. (2022). The

905   fourth industrial revolution in the food industry — Part I: Industry 4.0 technologies. *Critical Reviews

906   in Food Science and Nutrition*, *in press*. https://doi.org/10.1080/10408398.2022.2034735

907 Hassoun, Abdo, Aït-Kaddour, A., Sahar, A., & Cozzolino, D. (2021). Monitoring thermal treatments applied

908   to meat using traditional methods and spectroscopic techniques: A review of advances over the last

909   decade. *Food and Bioprocess Technology*, *14*, 195–208. https://doi.org/10.1007/s11947-020-02510-0

910   Hassoun, Abdo, Cropotova, J., Rustad, T., Heia, K., Lindberg, S.-K., & Nilsen, H. (2020). Use of

911   spectroscopic techniques for a rapid and non-destructive monitoring of thermal treatments and storage

912   time of sous-vide cooked cod fillets. *Sensors (Switzerland)*, *20*(8), 2410.

913   https://doi.org/10.3390/s20082410

914   Hassoun, Abdo, Gudjónsdóttir, M., Prieto, M. A., Garcia-Oliveira, P., Simal-Gandara, J., Marini, F., Di

915   Donato, F., D'Archivio, A. A., & Biancolillo, A. (2020). Application of novel techniques for

916   monitoring quality changes in meat and fish products during traditional processing processes:

917   Reconciling novelty and tradition. *Processes*, *8*(988), 1–20. https://doi.org/10.3390/PR8080988

918   Hassoun, Abdo, Heia, K., Lindberg, S. K., & Nilsen, H. (2020a). Performance of fluorescence and diffuse

919   reflectance hyperspectral imaging for characterization of lutefisk: A traditional norwegian fish dish.

920   *Molecules*, *25*(5). https://doi.org/10.3390/molecules25051191

921   Hassoun, Abdo, Heia, K., Lindberg, S., & Nilsen, H. (2020b). Spectroscopic techniques for monitoring

922   thermal treatments in fish and other seafood: A review of recent developments and applications. *Foods*,

923   *6*(9). https://doi.org/10.3390/foods9060767

924   Hassoun, Abdo, Måge, I., Schmidt, W. F., Temiz, H. T., Li, L., Kim, H.-Y., Nilsen, H., Biancolillo, A., Aït-

925   Kaddour, A., Sikorski, M., Sikorska, E., Grassi, S., & Cozzolino, D. (2020). Fraud in animal origin

926   food products: Advances in emerging spectroscopic detection methods over the past five years. *Foods*,

927   *9*(8), 1069. https://doi.org/10.3390/foods9081069

928   Hassoun, Abdo, Sahar, A., Lakhal, L., & Aït-Kaddour, A. (2019). Fluorescence spectroscopy as a rapid and

929   non-destructive method for monitoring quality and authenticity of fish and meat products: Impact of

930   different preservation conditions. *LWT*, 103, 279–292. https://doi.org/10.1016/j.lwt.2019.01.021

931   Hassoun, Abdo, Shumilina, E., Di Donato, F., Foschi, M., Simal-Gandara, J., & Biancolillo, A. (2020).

932   Emerging techniques for differentiation of fresh and frozen-thawed seafoods: Highlighting the

933   potential of spectroscopic techniques. *Molecules*, *25*(19). https://doi.org/10.3390/molecules25194472

934   Hassoun, Abdo, Siddiqui, S. A., Smaoui, S., Ucak, İ., Arshad, R. N., Garcia-Oliveira, P., Prieto, M. A., Aït-

935   Kaddour, A., Perestrelo, R., Câmara, J. S., & Bono, G. (2022). Seafood processing, preservation, and

936   analytical techniques in the age of Industry 4.0. *Applied Sciences*, *12*(3), 1703.

937   https://doi.org/10.3390/APP12031703

938   He, H.-J., Wu, D., & Sun, D.-W. (2014). Potential of hyperspectral imaging combined with chemometric

939   analysis for assessing and visualising tenderness distribution in raw farmed salmon fillets. *Journal of

940   Food Engineering*, *126*, 156–164. https://doi.org/10.1016/J.JFOODENG.2013.11.015

941   Higashi, B., Mariano, T. B., de Abreu Filho, B. A., Gonçalves, R. A. C., & de Oliveira, A. J. B. (2020).

942   Effects of fructans and probiotics on the inhibition of Klebsiella oxytoca and the production of short-

943   chain fatty acids assessed by NMR spectroscopy. *Carbohydrate Polymers*, *248*, 116832.

944   https://doi.org/10.1016/J.CARBPOL.2020.116832

945   Huh, S., Kim, H. J., Lee, S., Cho, J., Jang, A., & Bae, J. (2021). Utilization of electrical impedance

946   spectroscopy and image classification for non-invasive early assessment of meat freshness. *Sensors

947   (Switzerland)*, *21*(3), 1–13. https://doi.org/10.3390/s21031001

948   Ioana, A., & Korodi, A. (2021). DDS and OPC UA protocol coexistence solution in real-time and Industry

949   4.0 context using non-ideal infrastructure. *Sensors*, *21*(22), 7760. https://doi.org/10.3390/S21227760

950   ISO. (1981). *General methods of test and analysis of food products 67.050*.

951   Iymen, G., Tanriver, G., Hayirlioglu, Y. Z., & Ergen, O. (2020). Artificial intelligence-based identification

952   of butter variations as a model study for detecting food adulteration. *Innovative Food Science &

953   Emerging Technologies*, *66*, 102527. https://doi.org/10.1016/J.IFSET.2020.102527

954   Izquierdo-Llopart, A., & Saurina, J. (2019). Characterization of sparkling wines according to polyphenolic

955   profiles obtained by HPLC-UV/Vis and principal component analysis. *Foods*, *8*(1), 22.

956   https://doi.org/10.3390/FOODS8010022

957   Jagatheesaperumal, S. K., Rahouti, M., Ahmad, K., Al-Fuqaha, A., & Guizani, M. (2021). The duo of

958   artificial intelligence and big data for Industry 4.0: Review of applications, techniques, challenges, and

959   future research directions. *IEEE Internet of Things Journal*, *in press*, 1–33.

960   http://arxiv.org/abs/2104.02425

961   Jagtap, S., Bader, F., Garcia-Garcia, G., Trollman, H., Fadiji, T., & Salonitis, K. (2021). Food logistics 4.0:

962   Opportunities and challenges. *Logistics*, *5*(1), 2. https://doi.org/10.3390/LOGISTICS5010002

963   Jagtap, S., Garcia-Garcia, G., & Rahimifard, S. (2021). Optimisation of the resource efficiency of food

964   manufacturing via the Internet of Things. *Computers in Industry*, *127*, 103397.

965   https://doi.org/10.1016/J.COMPIND.2021.103397

966   Jambrak, A. R., Nutrizio, M., Djekić, I., Pleslić, S., & Chemat, F. (2021). Internet of nonthermal food

967   processing technologies (Iontp): Food industry 4.0 and sustainability. *Applied Sciences (Switzerland)*,

968   *11*(2), 1–20. https://doi.org/10.3390/app11020686

969   Javaid, M., Haleem, A., Pratap Singh, R., & Suman, R. (2021). Significance of Quality 4.0 towards

970   comprehensive enhancement in manufacturing sector. *Sensors International*, *2*, 100109.

971   https://doi.org/10.1016/J.SINTL.2021.100109

972   Jeevanandam, J., Agyei, D., Danquah, M. K., & Udenigwe, C. (2022). Food quality monitoring through

973   bioinformatics and big data. In Rajeev Bhat (Ed.), *Future Foods: Global Trends, Opportunities, and*

974   *Sustainability Challenges* (pp. 733–744). Academic Press. https://doi.org/10.1016/B978-0-323-

975   91001-9.00036-0

976   Jiang, H., Ru, Y., Chen, Q., Wang, J., & Xu, L. (2021). Near-infrared hyperspectral imaging for detection

977   and visualization of offal adulteration in ground pork. *Spectrochimica Acta Part A: Molecular and*

978   *Biomolecular Spectroscopy*, *249*, 119307. https://doi.org/10.1016/J.SAA.2020.119307

979   Jiang, H., Wang, W., Zhuang, H., Yoon, S. C., Yang, Y., & Zhao, X. (2019). Hyperspectral imaging for a

980   rapid detection and visualization of duck meat adulteration in beef. *Food Analytical Methods*, *12*(10),

981   2205–2215. https://doi.org/10.1007/s12161-019-01577-6

982   Jiang, L., Hassan, M. M., Ali, S., Li, H., Sheng, R., & Chen, Q. (2021). Evolving trends in SERS-based

983   techniques for food quality and safety: A review. *Trends in Food Science & Technology*, *112*, 225–

984   240. https://doi.org/10.1016/J.TIFS.2021.04.006

985   Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential

986   of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production

987   systems. *Current Opinion in Biotechnology*, *70*, 15–22.

988   https://doi.org/10.1016/J.COPBIO.2020.09.003

989   Kakani, V., Nguyen, V. H., Kumar, B. P., Kim, H., & Pasupuleti, V. R. (2020). A critical review on

990   computer vision and artificial intelligence in food industry. *Journal of Agriculture and Food Research*,

991   *2*, 100033. https://doi.org/10.1016/J.JAFR.2020.100033

992   Karuppuswami, S., Mondal, S., Kumar, D., & Chahal, P. (2020). RFID coupled passive digital ammonia

993   sensor for quality control of packaged food. *IEEE Sensors Journal*, *20*(9), 4679–4687.

994   https://doi.org/10.1109/JSEN.2020.2964676

995   Kassal, P., Steinberg, M. D., & Steinberg, I. M. (2018). Wireless chemical sensors and biosensors: A review.

996   *Sensors and Actuators, B: Chemical*, *266*, 228–245. https://doi.org/10.1016/j.snb.2018.03.074

997   Khaled, A. Y., Parrish, C. A., & Adedeji, A. (2021). Emerging nondestructive approaches for meat quality

998   and safety evaluation—A review. *Comprehensive Reviews in Food Science and Food Safety*, 1541-

999   4337.12781. https://doi.org/10.1111/1541-4337.12781

1000 Khan, P. W., Byun, Y. C., & Park, N. (2020). IoT-blockchain enabled optimized provenance system for

1001   food Industry 4.0 using advanced deep learning. *Sensors*, *20*(10), 2990.

1002   https://doi.org/10.3390/S20102990

1003 Konur, S., Lan, Y., Thakker, D., Morkyani, G., Polovina, N., & Sharp, J. (2021a). Towards design and

1004   implementation of Industry 4.0 for food manufacturing. *Neural Computing and Applications*,

1005   *0123456789*. https://doi.org/10.1007/s00521-021-05726-z

1006 Konur, S., Lan, Y., Thakker, D., Morkyani, G., Polovina, N., & Sharp, J. (2021b). Towards design and

1007   implementation of Industry 4.0 for food manufacturing. *Neural Computing and Applications*, 1–13.

1008   https://doi.org/10.1007/S00521-021-05726-Z/FIGURES/11

1009 Krause, J., Grüger, H., Gebauer, L., Zheng, X., Knobbe, J., Pügner, T., Kicherer, A., Gruna, R., Längle, T.,

1010   & Beyerer, J. (2021). SmartSpectrometer—Embedded optical spectroscopy for applications in

1011   agriculture and industry. *Sensors*, *21*(13), 4476. https://doi.org/10.3390/S21134476

1012   Krupitzer, C., & Stein, A. (2021). Food informatics -—— Review of the current state-of-the-art, revised

1013   definition, and classification into the research landscape. *Foods*, *10*(11), 2889.

1014   https://doi.org/10.3390/FOODS10112889

1015   Kumar, I., Rawat, J., Mohd, N., & Husain, S. (2021). Opportunities of artificial intelligence and machine

1016   learning in the food industry. *Journal of Food Quality*, *2021*. https://doi.org/10.1155/2021/4535567

1017   Kuś, P. M., Jerković, I., Marijanović, Z., Kranjac, M., & Tuberoso, C. I. G. (2018). Unlocking Phacelia

1018   tanacetifolia Benth. honey characterization through melissopalynological analysis, color

1019   determination and volatiles chemical profiling. *Food Research International*, *106*, 243–253.

1020   https://doi.org/10.1016/j.foodres.2017.12.065

1021   Kutsanedzie, F. Y. H., Guo, Z., & Chen, Q. (2019). Advances in nondestructive methods for meat quality

1022   and safety monitoring. *Food Reviews International*, *35*(6), 536–562.

1023   https://doi.org/10.1080/87559129.2019.1584814

1024   Lei, T., & Sun, D. W. (2019). Developments of nondestructive techniques for evaluating quality attributes

1025   of cheeses: A review. *Trends in Food Science and Technology*, *88*, 527–542.

1026   https://doi.org/10.1016/j.tifs.2019.04.013

1027   Li, D., Zhang, F., Yu, J., Chen, X., Liu, B., & Meng, X. (2021). A rapid and non-destructive detection of

1028   Escherichia coli on the surface of fresh-cut potato slices and application using hyperspectral imaging.

1029   *Postharvest Biology and Technology*, *171*, 111352.

1030   https://doi.org/10.1016/J.POSTHARVBIO.2020.111352

1031   Lintvedt, T. A., Andersen, P. V., Afseth, N. K., Marquardt, B., Gidskehaug, L., & Wold, J. P. (2022).

1032   Feasibility of in-line Raman spectroscopy for quality assessment in food industry: How fast can we

1033   go?: *Applied Spectroscopy*, 000370282110569. https://doi.org/10.1177/00037028211056931

1034   Liu, Y., Ma, D. hong, Wang, X. chang, Liu, L. ping, Fan, Y. xia, & Cao, J. xuan. (2015). Prediction of

1035   chemical composition and geographical origin traceability of Chinese export tilapia fillets products by

1036   near infrared reflectance spectroscopy. *LWT*, *60*(2), 1214–1218.

1037   https://doi.org/10.1016/j.lwt.2014.09.009

1038   Loizzo, M. R., Lucci, P., Núñez, O., Tundis, R., Balzano, M., Frega, N. G., Conte, L., Moret, S., Filatova,

1039   D., Moyano, E., & Pacetti, D. (2019). Native colombian fruits and their by-products: Phenolic profile,

1040   antioxidant activity and hypoglycaemic potential. *Foods* , *8*(3), 89.

1041   https://doi.org/10.3390/FOODS8030089

1042   Lorenzo, J. M., Domínguez, R., Pateiro, M., & Munekata, P. E. S. (2022). *Methods to assess the quality of*

1043   *meat products* (J. M. Lorenzo, R. Domínguez, M. Pateiro, & P. E. S. Munekata (eds.)). Springer.

1044   Lu, Y., Huang, Y., & Lu, R. (2017). Innovative hyperspectral imaging-based techniques for quality

1045   evaluation of fruits and vegetables: A review. *Applied Sciences*, *7*(2), 189.

1046   https://doi.org/10.3390/app7020189

1047   Ma, J., Sun, D.-W., Pu, H., Cheng, J.-H., & Wei, Q. (2019). Advanced techniques for hyperspectral imaging

1048   in the food industry: Principles and recent applications. *Annual Review of Food Science and*

1049   *Technology*, *10*(1). https://doi.org/10.1146/annurev-food-032818-121155

1050   Ma, J., Sun, D. W., Nicolai, B., Pu, H., Verboven, P., Wei, Q., & Liu, Z. (2019). Comparison of spectral

1051   properties of three hyperspectral imaging (HSI) sensors in evaluating main chemical compositions of

1052   cured pork. *Journal of Food Engineering*, *261*, 100–108.

1053   https://doi.org/10.1016/j.jfoodeng.2019.05.024

1054   Ma, P., Lau, C. P., Yu, N., Li, A., & Sheng, J. (2022). Application of deep learning for image-based Chinese

1055   market food nutrients estimation. *Food Chemistry*, *373*, 130994.

1056   https://doi.org/10.1016/J.FOODCHEM.2021.130994

1057   Mahanti, N. K., Pandiselvam, R., Kothakota, A., Ishwarya S., P., Chakraborty, S. K., Kumar, M., &

1058   Cozzolino, D. (2022). Emerging non-destructive imaging techniques for fruit damage detection: Image

1059   processing and analysis. *Trends in Food Science & Technology*, *120*, 418–438.

1060   https://doi.org/10.1016/J.TIFS.2021.12.021

1061 Malik, A. K., Blasco, C., & Picó, Y. (2010). Liquid chromatography–mass spectrometry in food safety.

1062   *Journal   of   Chromatography   A*,   *1217*(25),   4018–4040.

1063   https://doi.org/10.1016/J.CHROMA.2010.03.015

1064 Marvin, H. J. P., Bouzembrak, Y., van der Fels-Klerx, H. J., Kempenaar, C., Veerkamp, R., Chauhan, A.,

1065   Stroosnijder, S., Top, J., Simsek-Senel, G., Vrolijk, H., Knibbe, W. J., Zhang, L., Boom, R., &

1066   Tekinerdogan, B. (2022). Digitalisation and Artificial Intelligence for sustainable food systems.

1067   *Trends in Food Science & Technology*, *120*, 344–348. https://doi.org/10.1016/J.TIFS.2022.01.020

1068 Matt, D. T., Modrák, V., & Zsifkovits, H. Industry 4.0 for SMEs: Challenges, opportunities and

1069   requirements. Springer Nature. 2020. https://doi.org/10.1007/978-3-030-25425-4

1070 Mavani, N. R., Ali, J. M., Othman, S., Hussain, M. A., Hashim, H., & Rahman, N. A. (2021). Application

1071   of artificial intelligence in food industry—A guideline. *Food Engineering Reviews 2021 14:1*, *14*(1),

1072   134–175. https://doi.org/10.1007/S12393-021-09290-Z

1073 Maynard, A. D. (2015). Navigating the fourth industrial revolution. *Nature Nanotechnology*, *10*(12), 1005–

1074   1006. https://doi.org/10.1038/nnano.2015.286

1075 McVey, C., Elliott, C. T., Cannavan, A., Kelly, S. D., Petchkongkaew, A., & Haughey, S. A. (2021).

1076   Portable spectroscopy for high throughput food authenticity screening: Advancements in technology

1077   and integration into digital traceability systems. *Trends in Food Science & Technology*, *118*, 777–790.

1078   https://doi.org/10.1016/J.TIFS.2021.11.003

1079 Meenu, M., Kurade, C., Neelapu, B. C., Kalra, S., Ramaswamy, H. S., & Yu, Y. (2021). A concise review

1080   on food quality assessment using digital image processing. *Trends in Food Science & Technology*,

1081   *118*, 106–124. https://doi.org/10.1016/J.TIFS.2021.09.014

1082 Milovanovic, B., Djekic, I., Miocinovic, J., Djordjevic, V., Lorenzo, J. M., Barba, F. J., Mörlein, D., &

1083   Tomasevic, I. (2020). What is the color of milk and dairy products and how is it measured? *Foods*,

1084   *9*(11), 1629. https://doi.org/10.3390/foods9111629

1085   Mo, C., Kim, G., Kim, M. S., Lim, J., Cho, H., Barnaby, J. Y., & Cho, B. K. (2017). Fluorescence

1086   hyperspectral imaging technique for foreign substance detection on fresh-cut lettuce. *Journal of the*

1087   *Science of Food and Agriculture*, *97*(12), 3985–3993. https://doi.org/10.1002/jsfa.8262

1088   Modupalli, N., Naik, M., Sunil, C. K., & Natarajan, V. (2021). Emerging non-destructive methods for

1089   quality and safety monitoring of spices. *Trends in Food Science & Technology*, *108*, 133–147.

1090   https://doi.org/10.1016/J.TIFS.2020.12.021

1091   Müller-Maatsch, J., Bertani, F. R., Mencattini, A., Gerardino, A., Martinelli, E., Weesepoel, Y., & van Ruth,

1092   S. (2021). The spectral treasure house of miniaturized instruments for food safety, quality and

1093   authenticity applications: A perspective. *Trends in Food Science and Technology*, *110*, 841–848.

1094   https://doi.org/10.1016/j.tifs.2021.01.091

1095   Müller-Maatsch, J., & van Ruth, S. M. (2021). Handheld devices for food authentication and their

1096   applications: A review. *Foods*, *10*(12), 2901. https://doi.org/10.3390/FOODS10122901

1097   Munawar, A. A., Zulfahrizal, Meilina, H., & Pawelzik, E. (2022). Near infrared spectroscopy as a fast and

1098   non-destructive technique for total acidity prediction of intact mango: Comparison among regression

1099   approaches. *Computers and Electronics in Agriculture*, *193*, 106657.

1100   https://doi.org/10.1016/J.COMPAG.2021.106657

1101   Munson, C. R., Gao, Y., Mortimer, J. C., & Murray, D. T. (2022). Solid-state nuclear magnetic resonance

1102   as a tool to probe the impact of mechanical preprocessing on the structure and arrangement of plant

1103   cell wall polymers. *Frontiers in Plant Science*, *12*, 3013.

1104   https://doi.org/10.3389/FPLS.2021.766506/BIBTEX

1105   Muroya, S., Ueda, S., Komatsu, T., Miyakawa, T., & Ertbjerg, P. (2020). MEATabolomics: Muscle and

1106   meat metabolomics in domestic animals. *Metabolites*, *10*(5), 188.

1107   https://doi.org/10.3390/METABO10050188

1108   Nasirahmadi, A., & Hensel, O. (2022). Toward the next generation of digitalization in agriculture based on

1109   digital twin paradigm. *Sensors*, *22*(2), 498. https://doi.org/10.3390/S22020498

1110   Núñez, O., Moyano, E., & Galceran, M. T. (2005). LC–MS/MS analysis of organic toxics in food. *TrAC*

1111   *Trends in Analytical Chemistry*, *24*(7), 683–703. https://doi.org/10.1016/J.TRAC.2005.04.012

1112   Özdoğan, G., Lin, X., & Sun, D. W. (2021). Rapid and noninvasive sensory analyses of food products by

1113   hyperspectral imaging: Recent application developments. *Trends in Food Science and Technology*,

1114   *111*, 151–165. https://doi.org/10.1016/j.tifs.2021.02.044

1115   Pascua, Y., Koç, H., & Foegeding, E. A. (2013). Food structure: Roles of mechanical properties and oral

1116   processing in determining sensory texture of soft materials. *Current Opinion in Colloid and Interface*

1117   *Science*, *18*(4). 324–333. https://doi.org/10.1016/j.cocis.2013.03.009

1118   Pasquini, C. (2018). Near infrared spectroscopy: A mature analytical technique with new perspectives – A

1119   review. *Analytica Chimica Acta*, *1026*, 8–36. https://doi.org/10.1016/J.ACA.2018.04.004

1120   Pateiro, M., Purriños, L., Domínguez, R., Barretto, A. C. S., Munekata, P. E. S., Fraqueza, M. J., Pazos, A.

1121   A., & Lorenzo, J. M. (2022). Descriptive sensory analysis of meat—The baseline for any sensory

1122   innovation for meat products: Case study. In José M. Lorenzo, M. Pateiro, E. Saldaña, & P. E. S.

1123   Munekata (Eds.), *Sensory Analysis for the Development of Meat Products. Methodological Aspects*

1124   *and Practical Applications* (pp. 107–120). Woodhead Publishing.

1125   Pedrosa, M. C., Lima, L., Heleno, S., Carocho, M., Ferreira, I. C. F. R., & Barros, L. (2021). Food

1126   metabolites as tools for authentication, processing, and nutritive value assessment. *Foods* , *10*(9), 2213.

1127   https://doi.org/10.3390/FOODS10092213

1128   Picone, G., Mengucci, C., & Capozzi, F. (2022). The NMR added value to the green foodomics perspective:

1129   Advances by machine learning to the holistic view on food and nutrition. *Magnetic Resonance in*

1130   *Chemistry*. https://doi.org/10.1002/MRC.5257

1131   Ping, H., Wang, J., Ma, Z., & Du, Y. (2018). Mini-review of application of IoT technology in monitoring

1132   agricultural products quality and safety. *International Journal of Agricultural and Biological*

1133   *Engineering*, *11*(5), 35–45. https://doi.org/10.25165/j.ijabe.20181105.3092

1134   Pu, H., Lin, L., & Sun, D. W. (2019). Principles of hyperspectral microscope imaging techniques and their

applications in food quality and safety detection: A review. *Comprehensive Reviews in Food Science and Food Safety*, *00*, 1–14. https://doi.org/10.1111/1541-4337.12432

Purriños, L., Pateiro, M., Rosmini, M., Domínguez, R., Teixeira, A., Munekata, P. E. S., Campagnold, P. C. B., & Lorenzo, J. M. (2022). Descriptive sensory analysis as an analytical tool for the sensory characterization of meat products: Fundaments, panel training, and descriptors of meat products. In José M. Lorenzo, M. Pateiro, E. Saldaña, & P. E. S. Munekata (Eds.), *Sensory Analysis for the Development of Meat Products. Methodological Aspects and Practical Applications* (pp. 51–76). Woodhead Publishing.

Putnik, P., Kresoja, Ž., Bosiljkov, T., Režek Jambrak, A., Barba, F. J., Lorenzo, J. M., Roohinejad, S., Granato, D., Žuntar, I., & Bursać Kovačević, D. (2019). Comparing the effects of thermal and non-thermal technologies on pomegranate juice quality: A review. *Food Chemistry*, *279*, 150–161. https://doi.org/10.1016/j.foodchem.2018.11.131

Qian, J., Dai, B., Wang, B., Zha, Y., & Song, Q. (2022). Traceability in food processing: problems, methods, and performance evaluations—a review. *Critical Reviews in Food Science and Nutrition*, *62*(3), 679–692. https://doi.org/10.1080/10408398.2020.1825925

Qin, J., Vasefi, F., Hellberg, R. S., Akhbardeh, A., Isaacs, R. B., Yilmaz, A. G., Hwang, C., Baek, I., Schmidt, W. F., & Kim, M. S. (2020). Detection of fish fillet substitution and mislabeling using multimode hyperspectral imaging techniques. *Food Control*, *114*. https://doi.org/10.1016/j.foodcont.2020.107234

Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics*, *224*, 107546. https://doi.org/10.1016/J.IJPE.2019.107546

Rejeb, A., Keogh, J. G., Zailani, S., Treiblmaier, H., & Rejeb, K. (2020). Blockchain technology in the food industry: A review of potentials, challenges and future research directions. *Logistics*, *4*(4), 27.

https://doi.org/10.3390/LOGISTICS4040027

Ren, Q.-S., Fang, K., Yang, X.-T., & Han, J.-W. (2022). Ensuring the quality of meat in cold chain logistics: A comprehensive review. *Trends in Food Science & Technology*, *119*, 133–151. https://doi.org/10.1016/J.TIFS.2021.12.006

Reyrolle, M., Ghislain, M., Bru, N., Vallverdu, G., Pigot, T., Desauziers, V., & Le Bechec, M. (2022). Volatile fingerprint of food products with untargeted SIFT-MS data coupled with mixOmics methods for profile discrimination: Application case on cheese. *Food Chemistry*, *369*, 130801. https://doi.org/10.1016/J.FOODCHEM.2021.130801

Rifna, E. J., Pandiselvam, R., Kothakota, A., Subba Rao, K. V., Dwivedi, M., Kumar, M., Thirumdas, R., & Ramesh, S. V. (2022). Advanced process analytical tools for identification of adulterants in edible oils – A review. *Food Chemistry*, *369*, 130898. https://doi.org/10.1016/J.FOODCHEM.2021.130898

Rodriguez-Saona, L., Aykas, D. P., Borba, K. R., & Urtubia, A. (2020). Miniaturization of optical sensors and their potential for high-throughput screening of foods. *Current Opinion in Food Science*, *31*, 136–150. https://doi.org/10.1016/j.cofs.2020.04.008

Rosin, F., Forget, P., Lamouri, S., & Pellerin, R. (2019). Impacts of Industry 4.0 technologies on Lean principles. *International Journal of Production Research*, *58*(6), 1644–1661. https://doi.org/10.1080/00207543.2019.1672902

Ruiz-Capillas, C., Herrero, A. M., Pintado, T., & Delgado-Pando, G. (2021). Sensory analysis and consumer research in new meat products development. *Foods*, *10*(2), 429. https://doi.org/10.3390/foods10020429

Rüßmann, M. et al. (2015). Future of productivity and growth in manufacturing. *Boston Consulting*, *9*(1), 54–89. https://doi.org/10.1007/s12599-014-0334-4

Saadat, S., Pandya, H., Dey, A., & Rawtani, D. (2022). Food forensics: Techniques for authenticity determination of food products. *Forensic Science International*, *333*, 111243. https://doi.org/10.1016/J.FORSCIINT.2022.111243

1185   Saberioon, M., Gholizadeh, A., Cisar, P., Pautsina, A., & Urban, J. (2017). Application of machine vision

1186   systems in aquaculture with emphasis on fish: State-of-the-art and key issues. *Reviews in Aquaculture*,

1187   *9*(4), 369–387. https://doi.org/10.1111/raq.12143

1188   Sader, S., Husti, I., & Daroczi, M. (2021). A review of quality 4.0: definitions, features, technologies,

1189   applications,   and   challenges.   *Total   Quality   Management   &   Business   Excellence*.

1190   https://doi.org/10.1080/14783363.2021.1944082

1191   Saha, D., & Manickavasagan, A. (2021). Machine learning techniques for analysis of hyperspectral images

1192   to determine quality of food products: A review. *Current Research in Food Science*, *4*, 28–44.

1193   https://doi.org/10.1016/J.CRFS.2021.01.002

1194   Sarkar, T., Salauddin, M., Kirtonia, K., Pati, S., Rebezov, M., Khayrullin, M., Panasenko, S., Tretyak, L.,

1195   Temerbayeva, M., Kapustina, N., Azimova, S., Gruzdeva, L., Makhmudov, F., Nikitin, I., Kassenov,

1196   A., Shariati, M. A., & Lorenzo, J. M. (2022). A review on the commonly used methods for analysis of

1197   physical   properties   of   food   materials.   *Applied   Sciences*,   *12*(4),   2004.

1198   https://doi.org/10.3390/APP12042004

1199   Savina, A., Malyavkina, L., Baturina, N., Bolshakova, L., Zimina, L., & Vlasova, M. (2020). Information

1200   and technological support of the system of food quality and safety management in the digital

1201   economical   environment.   *ACM   International   Conference   Proceeding   Series*.

1202   https://doi.org/10.1145/3446434.3446443

1203   Serazetdinova, L., Garratt, J., Baylis, A., Stergiadis, S., Collison, M., & Davis, S. (2019). How should we

1204   turn data into decisions in AgriFood? *Journal of the Science of Food and Agriculture*, *99*(7), 3213–

1205   3219. https://doi.org/10.1002/JSFA.9545

1206   Shi, C., Qian, J., Zhu, W., Liu, H., Han, S., & Yang, X. (2019). Nondestructive determination of freshness

1207   indicators for tilapia fillets stored at various temperatures by hyperspectral imaging coupled with RBF

1208   neural networks. *Food Chemistry*, *275*, 497–503. https://doi.org/10.1016/J.FOODCHEM.2018.09.092

1209   Silva, L. K. R., Santos, L. S., Ferr, S. P. B., & Ao, ~. (2022). Application of infrared spectroscopic

techniques to cheese authentication: A review. *International Journal of Dairy Technology.* https://doi.org/10.1111/1471-0307.12859

Singh, D., Chaudhary, P., Taunk, J., Singh, C. K., Singh, D., Tomar, R. S. S., Aski, M., Konjengbam, N. S., Raje, R. S., Singh, S., Sengar, R. S., Yadav, R. K., & Pal, M. (2021). *Fab* advances in *Fabaceae* for abiotic stress resilience: From 'Omics' to artificial intelligence. *International Journal of Molecular Sciences*, *22*(19), 10535. https://doi.org/10.3390/IJMS221910535

Song, S., Liu, Z., Huang, M., Zhu, Q., Qin, J., & Kim, M. S. (2020). Detection of fish bones in fillets by Raman hyperspectral imaging technology. *Journal of Food Engineering*, *272*, 109808. https://doi.org/10.1016/J.JFOODENG.2019.109808

Sony, M., & Naik, S. (2020). Key ingredients for evaluating Industry 4.0 readiness for organizations: A literature review. *Benchmarking*, *27*(7), 2213–2232. https://doi.org/10.1108/BIJ-09-2018-0284

Squeo, G., De Angelis, D., Summo, C., Pasqualone, A., Caponio, F., & Amigo, J. M. (2022). Assessment of macronutrients and alpha-galactosides of texturized vegetable proteins by near infrared hyperspectral imaging. *Journal of Food Composition and Analysis*, *108*, 104459. https://doi.org/10.1016/J.JFCA.2022.104459

Stasenko, N., Chernova, E., Shadrin, D., Ovchinnikov, G., Krivolapov, I., & Pukalchik, M. (2021). Deep Learning for improving the storage process: Accurate and automatic segmentation of spoiled areas on apples. *Conference Record - IEEE Instrumentation and Measurement Technology Conference*, *2021*. https://doi.org/10.1109/I2MTC50364.2021.9460071

Su, W. H., & Sun, D. W. (2019). Mid-infrared (MIR) spectroscopy for quality analysis of liquid foods. *Food Engineering Reviews*, *11*(3), 142–158. https://doi.org/10.1007/s12393-019-09191-2

Tan, X., Ye, Y., Liu, H., Meng, J., Yang, L. L., & Li, F. (2022). Deep learning-assisted visualized fluorometric sensor array for biogenic amines detection. *Chinese Journal of Chemistry*, *40*(5), 609–616. https://doi.org/10.1002/CJOC.202100591

Tomasevic, I., Tomovic, V., Milovanovic, B., Lorenzo, J., Đorđević, V., Karabasil, N., & Djekic, I. (2019).

1235   Comparison of a computer vision system vs. traditional colorimeter for color evaluation of meat

1236   products with various physical properties. *Meat Science*, *148*, 5–12.

1237   https://doi.org/10.1016/j.meatsci.2018.09.015

1238   Tramuta, C., Decastelli, L., Barcucci, E., Ingravalle, F., Fragassi, S., Lupi, S., & Bianchi, D. M. (2022).

1239   Detection of peanut traces in food by an official food safety laboratory. *Foods* , *11*(5), 643.

1240   https://doi.org/10.3390/FOODS11050643

1241   Troy, D. J., Ojha, K. S., Kerry, J. P., & Tiwari, B. K. (2016). Sustainable and consumer-friendly emerging

1242   technologies for application within the meat industry: An overview. *Meat Science*, *120*, 2–9.

1243   https://doi.org/10.1016/J.MEATSCI.2016.04.002

1244   Valdés, A., Álvarez-Rivera, G., Socas-Rodríguez, B., Herrero, M., & Cifuentes, A. (2022). Capillary

1245   electromigration methods for food analysis and Foodomics: Advances and applications in the period

1246   February 2019–February 2021. *Electrophoresis*, *43*(1–2), 37–56.

1247   https://doi.org/10.1002/ELPS.202100201

1248   Valdés, A., Álvarez-Rivera, G., Socas-Rodríguez, B., Herrero, M., Ibáñez, E., & Cifuentes, A. (2021).

1249   Foodomics: Analytical opportunities and challenges. *Analytical Chemistry*, *94*(1), 366–381.

1250   https://doi.org/10.1021/ACS.ANALCHEM.1C04678

1251   Van De Looverbosch, T., Raeymaekers, E., Verboven, P., Sijbers, J., & Nicolaï, B. (2021). Non-destructive

1252   internal disorder detection of Conference pears by semantic segmentation of X-ray CT scans using

1253   deep learning. *Expert Systems with Applications*, *176*, 114925.

1254   https://doi.org/10.1016/J.ESWA.2021.114925

1255   Vernier, C., Loeillet, D., Thomopoulos, R., & Macombe, C. (2021). Adoption of ICTs in Agri-Food

1256   logistics: Potential and limitations for supply chain sustainability. *Sustainability*, *13*(12), 6702.

1257   https://doi.org/10.3390/SU13126702

1258   Wang, B., Sun, J., Xia, L., Liu, J., Wang, Z., Li, P., Guo, Y., & Sun, X. (2021). The applications of

1259   hyperspectral imaging technology for agricultural products quality analysis: A review. *Food Reviews*

1260   *International*. https://doi.org/10.1080/87559129.2021.1929297

1261   Wang, H., Lan, Y., Kong, F., & Weng, L. (2020). Fresh agricultural products cold chain location selection

1262   in context of big data. *Journal of Physics: Conference Series*, *1631*(1), 012122.

1263   https://doi.org/10.1088/1742-6596/1631/1/012122

1264   Wang, K., Pu, H., & Sun, D. W. (2018). Emerging spectroscopic and spectral imaging techniques for the

1265   rapid detection of microorganisms: An overview. *Comprehensive Reviews in Food Science and Food*

1266   *Safety*, *17*(2), 256–273. https://doi.org/10.1111/1541-4337.12323

1267   Wang, W., Ye, Z., Gao, H., & Ouyang, D. (2021). Computational pharmaceutics - A new paradigm of drug

1268   delivery. *Journal of Controlled Release*, *338*, 119–136.

1269   https://doi.org/10.1016/J.JCONREL.2021.08.030

1270   Wang, X., Shan, J., Han, S., Zhao, J., & Zhang, Y. (2019). Optimization of fish quality by evaluation of

1271   total volatile basic nitrogen (TVB-N) and texture profile analysis (TPA) by near-infrared (NIR)

1272   hyperspectral imaging. *Analytical Letters*, *52*(12), 1845–1859.

1273   https://doi.org/10.1080/00032719.2019.1571077

1274   Wieczorek, D., Żyszka-haberecht, B., Kafka, A., & Lipok, J. (2021). Phosphonates as unique components

1275   of plant seeds—A promising approach to use phosphorus profiles in plant chemotaxonomy.

1276   *International Journal of Molecular Sciences*, *22*(21), 11501. https://doi.org/10.3390/IJMS222111501

1277   Wold, J. P. (2016). On-line and non-destructive measurement of core temperature in heat treated fish cakes

1278   by NIR hyperspectral imaging. *Innovative Food Science and Emerging Technologies*, *33*, 431–437.

1279   https://doi.org/10.1016/j.ifset.2015.12.012

1280   Wu, Z., Pu, H., & Sun, D. W. (2021). Fingerprinting and tagging detection of mycotoxins in agri-food

1281   products by surface-enhanced Raman spectroscopy: Principles and recent applications. *Trends in Food*

1282   *Science & Technology*, *110*, 393–404. https://doi.org/10.1016/J.TIFS.2021.02.013

1283   Xie, C., Chu, B., & He, Y. (2018). Prediction of banana color and firmness using a novel wavelengths

1284   selection method of hyperspectral imaging. *Food Chemistry*, *245*, 132–140.

1285 https://doi.org/10.1016/J.FOODCHEM.2017.10.079

1286 Xu, J.-L., Riccioli, C., & Sun, D.-W. (2016). Efficient integration of particle analysis in hyperspectral

1287 imaging for rapid assessment of oxidative degradation in salmon fillet. *Journal of Food Engineering*,

1288 *169*, 259–271. https://doi.org/10.1016/J.JFOODENG.2015.08.015

1289 Xu, L., Yang, F., Dias, A. C. P., & Zhang, X. (2022). Development of quantum dot-linked immunosorbent

1290 assay (QLISA) and ELISA for the detection of sunset yellow in foods and beverages. *Food Chemistry*,

1291 *385*, 132648. https://doi.org/10.1016/J.FOODCHEM.2022.132648

1292 Xu, M., Sun, J., Yao, K., Cai, Q., Shen, J., Tian, Y., & Zhou, X. (2022). Developing deep learning based

1293 regression approaches for prediction of firmness and pH in Kyoho grape using Vis/NIR hyperspectral

1294 imaging. *Infrared Physics & Technology*, *120*, 104003.

1295 https://doi.org/10.1016/J.INFRARED.2021.104003

1296 Xu, S., Zhao, X., & Liu, Z. (2020). The impact of blockchain technology on the cost of food traceability

1297 supply chain. *IOP Conference Series: Earth and Environmental Science*, *615*(1), 012003.

1298 https://doi.org/10.1088/1755-1315/615/1/012003

1299 Xu, Z., Cheng, W., Fan, S., Liu, J., Wang, H., Li, X., Liu, B., Wu, Y., Zhang, P., & Wang, Q. (2022). Data

1300 fusion of near-infrared diffuse reflectance spectra and transmittance spectra for the accurate

1301 determination of rice flour constituents. *Analytica Chimica Acta*, *1193*, 339384.

1302 https://doi.org/10.1016/J.ACA.2021.339384

1303 Yao, K., Sun, J., Chen, C., Xu, M., Zhou, X., Cao, Y., & Tian, Y. (2022). Non-destructive detection of egg

1304 qualities based on hyperspectral imaging. *Journal of Food Engineering*, *325*, 111024.

1305 https://doi.org/10.1016/J.JFOODENG.2022.111024

1306 Yoo, H., Park, D. (2021). AI-based 3D food printing using standard composite materials. In: Kim, J., Lee,

1307 R. (eds) *data science and digital transformation in the fourth industrial revolution. studies in*

1308 *computational intelligence*. Springer, Cham. https://doi.org/10.1007/978-3-030-64769-8_10

1309 Yu, X., Wang, J., Wen, S., Yang, J., & Zhang, F. (2019). A deep learning based feature extraction method

1310   on hyperspectral images for nondestructive prediction of TVB-N content in Pacific white shrimp

1311   (*Litopenaeus vannamei*). *Biosystems Engineering*, *178*, 244–255.

1312   https://doi.org/10.1016/J.BIOSYSTEMSENG.2018.11.018

1313   Zaukuu, J. L. Z., Benes, E., Bázár, G., Kovács, Z., & Fodor, M. (2022). Agricultural potentials of molecular

1314   spectroscopy and advances for food authentication: An overview. *Processes* , *10*(2), 214.

1315   https://doi.org/10.3390/PR10020214

1316   Zeba, G., Dabić, M., Čičak, M., Daim, T., & Yalcin, H. (2021). Technology mining: Artificial intelligence

1317   in manufacturing. *Technological Forecasting and Social Change*, *171*, 120971.

1318   https://doi.org/10.1016/J.TECHFORE.2021.120971

1319   Zhang, Y., Wang, X., Shan, J., Zhao, J., Zhang, W., Liu, L., & Wu, F. (2019). Hyperspectral imaging based

1320   method for rapid detection of microplastics in the intestinal tracts of fish. *Environmental Science and*

1321   *Technology*, *53*(9), 5151–5158. https://doi.org/10.1021/acs.est.8b07321

1322   Zhao, T., Feng, A., Jin, S., Shi, Y., Hou, B., Yan, Y. (2020). Research progress on artificial intelligence

1323   human sensor. In: Peng, Y., Dong, X. (eds) *Proceedings of 2018 International Conference on*

1324   *Optoelectronics and Measurement. Lecture Notes in Electrical Engineering*. Springer, Singapore.

1325   https://doi.org/10.1007/978-981-13-8595-7_35

1326   Zheng, M., Zhang, S., Zhang, Y., & Hu, B. (2021). Construct food safety traceability system for people's

1327   health under the Internet of Things and big data. *IEEE Access*, *9*, 70571–70583.

1328   https://doi.org/10.1109/ACCESS.2021.3078536

1329   Zhou, B., Fan, X., Song, J., Wu, J., Pan, L., Tu, K., Peng, J., Dong, Q., Xu, J., & Wu, J. (2022). Growth

1330   simulation of Pseudomonas fluorescens in pork using hyperspectral imaging. *Meat Science*, *188*,

1331   108767. https://doi.org/10.1016/J.MEATSCI.2022.108767

1332   Zhou, L., Tan, L., Zhang, C., Zhao, N., He, Y., & Qiu, Z. (2022). A portable NIR-system for mixture

1333   powdery food analysis using deep learning. *LWT*, *153*, 112456.

1334   https://doi.org/10.1016/J.LWT.2021.112456

1335   Zhuang, Q., Peng, Y., Yang, D., Wang, Y., Zhao, R., Chao, K., & Guo, Q. (2022). Detection of frozen pork

1336   freshness by fluorescence hyperspectral image. *Journal of Food Engineering*, *316*, 110840.

1337   https://doi.org/10.1016/J.JFOODENG.2021.110840

1338   Zhuangzhuang, L. (2020). Study on the construction of traceability system of cold-chain agricultural

1339   products based on block-chain: A case study of Ningxia Cabbage. *Proceedings - 2020 International*

1340   *Conference on Big Data and Artificial Intelligence and Software Engineering, ICBASE 2020*, 270–

1341   274. https://doi.org/10.1109/ICBASE51474.2020.00063

1342

1343

1344   **Figure Captions**

1345

1346   **Fig. 1.** Number of publications and citations per year (until June 06, 2022) related to the application

1347   of digitalization and automation in the food quality.

1348   **Fig. 2.** Building blocks of Industry 4.0.

1349   **Fig. 3.** Some factors to assess Industry 4.0 readiness for businesses.

1350   **Fig. 4.** Traditional methods *vs.* emerging techniques used in the food quality determination**.**

1351   **Legend:** IRMS: Isotope Ratio Mass Spectrometry; MALDI-TOF-MS: Matrix-Assisted

1352   Laser Desorption Ionization coupled to Time-of-Flight Mass Spectrometry; NMR: Nuclear

1353   Magnetic Resonance spectroscopy; PTR: Proton Transfer Reaction; REIMS: Rapid

1354   Evaporative Ionization Mass Spectrometry.

1355   **Fig. 5.** Common high-throughput analytical techniques taken as gold standards for food quality

1356   assessment and safety monitoring.

1357

1358   **Table 1**. Use of hyperspectral imaging in various foods quality-related applications

Food	Objective	Spectral Range	Main results	Reference
American bison (*Bison bison*)	Classification of muscles according to ageing period and retail display period, and prediction of color parameters	400-1000 nm	Satisfactory classification results were obtained using PLS-DA model. Redness value (*a* value*) was successfully predicted using PLSR model.	(Chaudhry et al., 2021)
Pacific white shrimp (*Litopenaeusvannamei*)	Prediction of TVB-N	900-1700 nm	After extracting spectral features by deep learning algorithms, LS-SVM model predicted TVB-N with satisfactory accuracy.	(Yu et al., 2019)
	Prediction of TVB-N	860-1700 nm	After building PLSR models with six various pretreatments algorithms, the one built with multiple scattering correction gave the best results. A graphical user interface system was developed to predict the freshness.	(Guo et al., 2021)
Grass carp (*Ctenopharyngodonidella*)	Prediction of TVB-N	308-1105 nm	The best TVB-N prediction result was obtained using PLSR model applied to six optimal wavelengths, selected by a novel algorithm called *Physarum* network combined with genetic algorithm.	(Cheng et al., 2017)
	Detection of fish bones in natural fish fillets	Raman: Excitation; 785 nm line laser (covering a Raman shift range from 820 cm^{-1} - 2847 cm^{-1})	Support vector data description classification model was built on optimal band information, selected using a fuzzy-rough set model, yielding a detection performance of 90.5% with a depth of up to 2.5 mm.	(Song et al., 2020)
Pork	Prediction of TVB-N	842–2532 nm	The PLSR model optimized using random frog (wavelength selection method) and maximum normalization (preprocessing method) showed the best prediction results.	(Baek et al., 2021)
	Prediction of several freshness parameters in frozen pork	Fluorescence: Excitation at 365 nm and emission at 400-1000 nm Vis/NIR: 400–1000 nm	The PLSR model established on the fluorescence data showed good performances in predicting freshness attributes (TVB-N, pH, and color parameters) in frozen samples without thawing.	(Zhuang et al., 2022)

59

	Prediction of microbial growth	400–1000 nm	A high correlation coefficient between the growth models of *Pseudomonas fluorescens* established using HSI and the plate count method.	(Zhou et al., 2022)
	Detection of offal adulteration in ground pork	400–1000 nm	Good prediction performances were achieved using PLSR models established on eleven featured wavelengths. Limit of detection less than 10 % was obtained.	(Jiang et al., 2021)
Cured pork	Prediction of chemical composition	400-1000 nm	The PLSR model based on nine wavelengths enabled good prediction performances of moisture, protein, and fat contents with R^2 values of respectively 0.8294, 0.8909, and 8241.	(Ma, Sun, Nicolai, et al., 2019)
Atlantic salmon (*Salmo salar*)	Prediction of TBARS and pH	900-1700 nm	Feature wavelengths were selected for developing multispectral imaging system. A satisfactory performance of TBARS prediction model was obtained, enabling a rapid assessment of oxidative degradation.	(Xu et al., 2016)
	Prediction of tenderness	400-1720 nm	Warner–Bratzler shear was predicted with good accuracy by LS-SVM models established on four wavelengths, selected using successful projections algorithm.	(He et al., 2014)
Traditional dry-cured pork belly	Prediction of TBARS as a lipid oxidation indicator	400-1000 nm	Acceptable prediction results of TBARS were obtained using PLSR models established following first and second derivatives pretreatments.	(Aheto et al., 2020)
Crucian carp	Prediction of TVB-N and TPA	900-1700 nm	The PLSR models built on spectral data and textural features, extracted from fish eyes and gills to predict TVB-N and TPA, respectively, show high accuracy.	(Wang et al., 2019)
	Detection of micro plastics in the intestinal tracts	900-1700 nm	SVM classification model was developed, showing promising efficiency and satisfying detection accuracy on three marine fish species.	(Zhang et al., 2019)
Beef, lamb and venison samples including different muscle type	Prediction of intramuscular fat and pH	548 - 1701 nm	PLSR and deep convolutional neural networks models showed good prediction performances.	(Dixit et al., 2021)
Tilapia	Prediction of 4 freshness parameters;	325-1098 nm	A new neural network algorithm (called radial basis function neural networks) was developed	(Shi et al., 2019)

	TVB-N, total aerobic count, *K value*, and sensory evaluation		using nine wavelengths selected by the successive projection algorithm, and the optimized model provided accurate prediction of the 4 freshness indicators.	
Fish cakes	Prediction of core temperature	760-1040 nm	A good prediction model was established giving a root mean square error of prediction of 2.3 °C, even down to 11–13 mm depth.	(Wold, 2016)
Japanese Big Sausages	Determination of pH of cooked sausages after different storage conditions	380 -1000 nm	The PLSR model built on the optimal wavelengths showed good prediction precision (R^2 0.909 and the root mean square error of prediction 0.035).	(Feng et al., 2018)
Potato slices	Prediction of foodborne pathogens (*Escherichia coli*) on the surface of fresh-cut products	400-1000 nm	*E. coli* was predicted with back-propagation neural network model giving a good accuracy ($R^2 = 0.976$).	(Li et al., 2021)
Plant-based meat analogues	Prediction of proximate composition and alpha-galactosides content	950−1654 nm	A robust prediction of the chemical composition was achieved using PLSR models, and pixel-by-pixel prediction allowed the tracking of components distribution.	(Squeo et al., 2022)
Kyoho grape (*Vitis labruscana cv. Kyoho*)	Prediction of firmness and pH	400-1000 nm	Deep features, extracted via a deep learning approach (called Stacked auto-encoders), were used to build a LS-SVM, achieving an optimal prediction performance for firmness and satisfactory accuracy for pH.	(Xu et al., 2022)
Banana (*Musa spp., AAA group cv. 'Brazil'*)	Prediction of color parameters and firmness	380-1023 nm	Color parameters ($L*$, $a*$ and $b*$) and firmness were predicted with acceptable accuracy using PLSR models. Excellent classification results of ripe and unripe banana were achieved.	(Xie et al., 2018)
Beef	Detection of adulteration of beef with duck meat	380-1012 nm	Good performance of predicted values of adulteration levels using PLRS models was achieved. Adulteration maps in the samples with different adulteration levels were generated, enhancing the visual appearance of adulteration.	(Jiang et al., 2019)
Cod	Characterization of lutefisk and classification of four brands	Fluorescence: Excitation at 365 nm and emission at 430-1000 nm	High performance for the discrimination between samples of four different brands of lutefisk using PLR-DA applied on fluorescence data.	(Hassoun, Heia, et al., 2020a)

Lamb, beef, and pork	Authentication and classification of meat species	548-1701 nm	Spectral and spatial information, integrated into deep convolutional neural network models, provided a stable accuracy on line-scanning and snapshot HSI images.	(Al-Sarayreh et al., 2020)
Pearl Gentian Grouper	Detection of freshness of fish stored under different conditions	900-1700 nm	Classification accuracies of 100%, 96.43%, and 96.43% were obtained for respectively fresh, refrigerated, and frozen thawed fish. PLSR models used to predict storage time achieved high modeling and prediction accuracy.	(Chen et al., 2021)
Lettuce	Detection of foreign substances	Fluorescence: Excitation at 365 nm and emission at 430-700 nm	Prediction accuracy of 95.87% for worm detection was obtained, with best classification accuracy being achieved using spectral images with a pixel size of 1×1mm.	(Mo et al., 2017)
Cod (*Gadus morhua L.*)	Monitoring thermal treatments and storage time	Fluorescence: Excitation at 365 nm and emission at 430-1000 nm	Fluorescence intensity was decreased with increasing cooking temperature and storage time. Classification accuracy of 92.5% was obtained.	(Hassoun et al., 2020)

1359 TVB-N: Total volatile basic nitrogen; HSI: Hyperspectral imaging; PLS-DA: Partial least square discrimination analysis; PLSR: Partial least squares regression;
1360 LS-SVM: Least-squares support vector machine; TPA: Texture profile analysis; TBARS: Thiobarbituric acid reactive substance; Vis/NIR: Visible/Near infrared
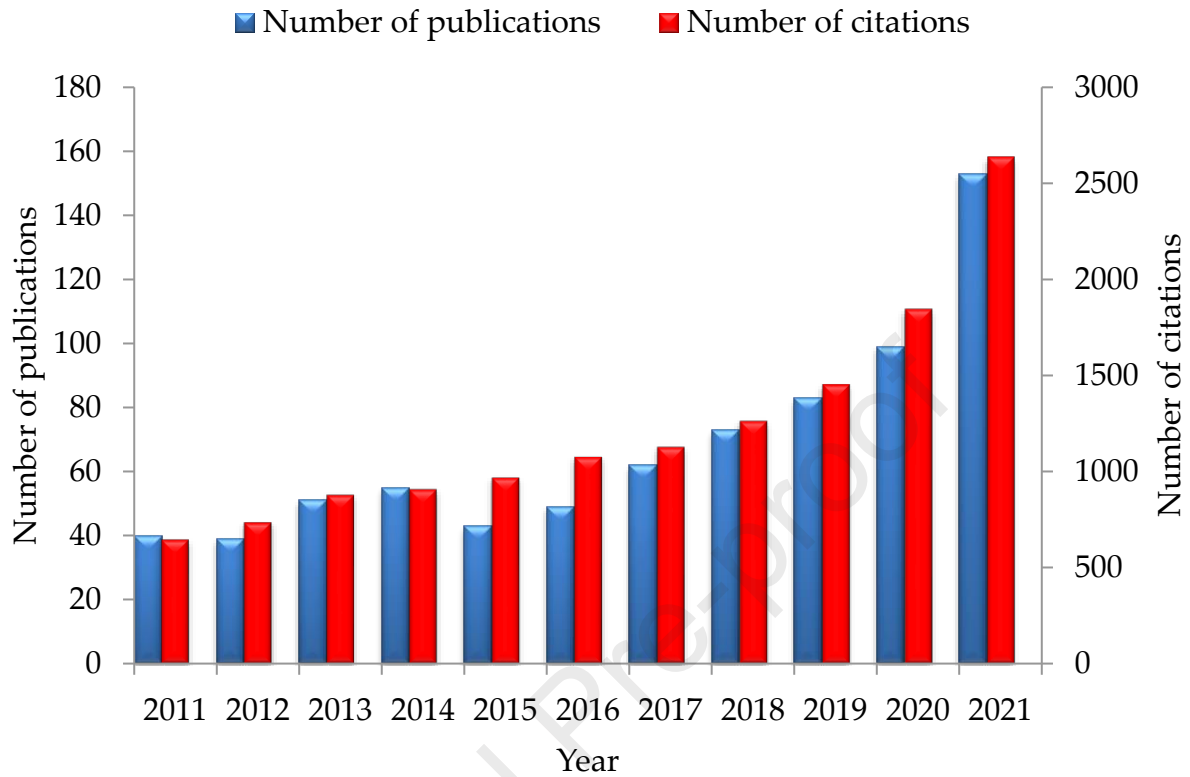1361

1362

1363

1364

1365

1366

1367

1368

1369

1370
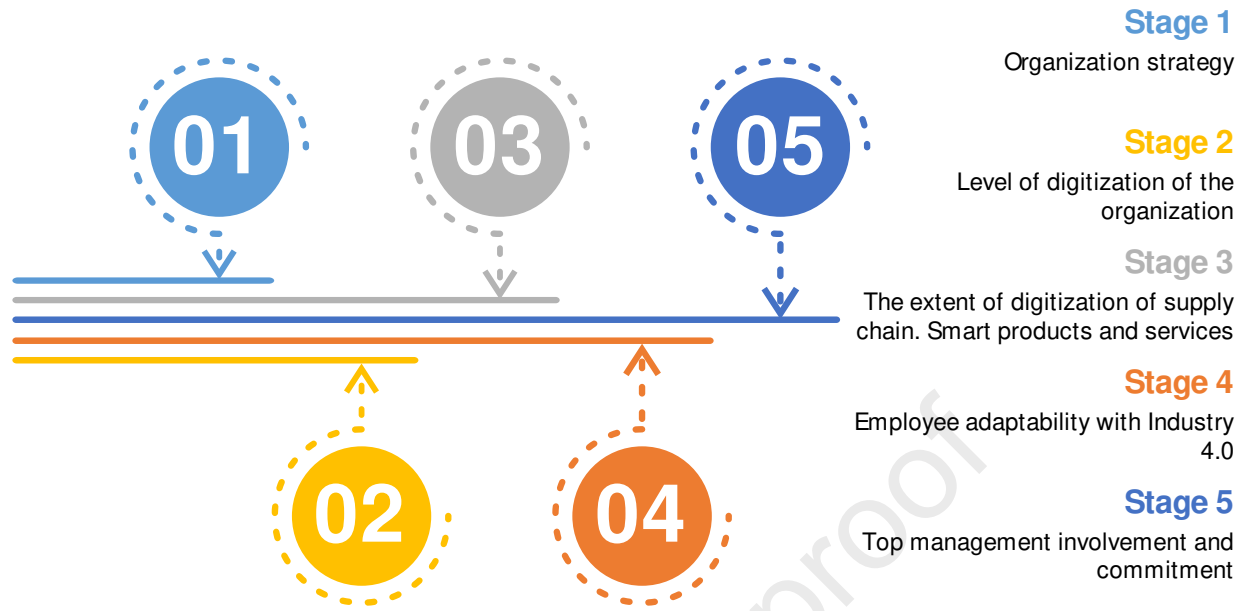

1371
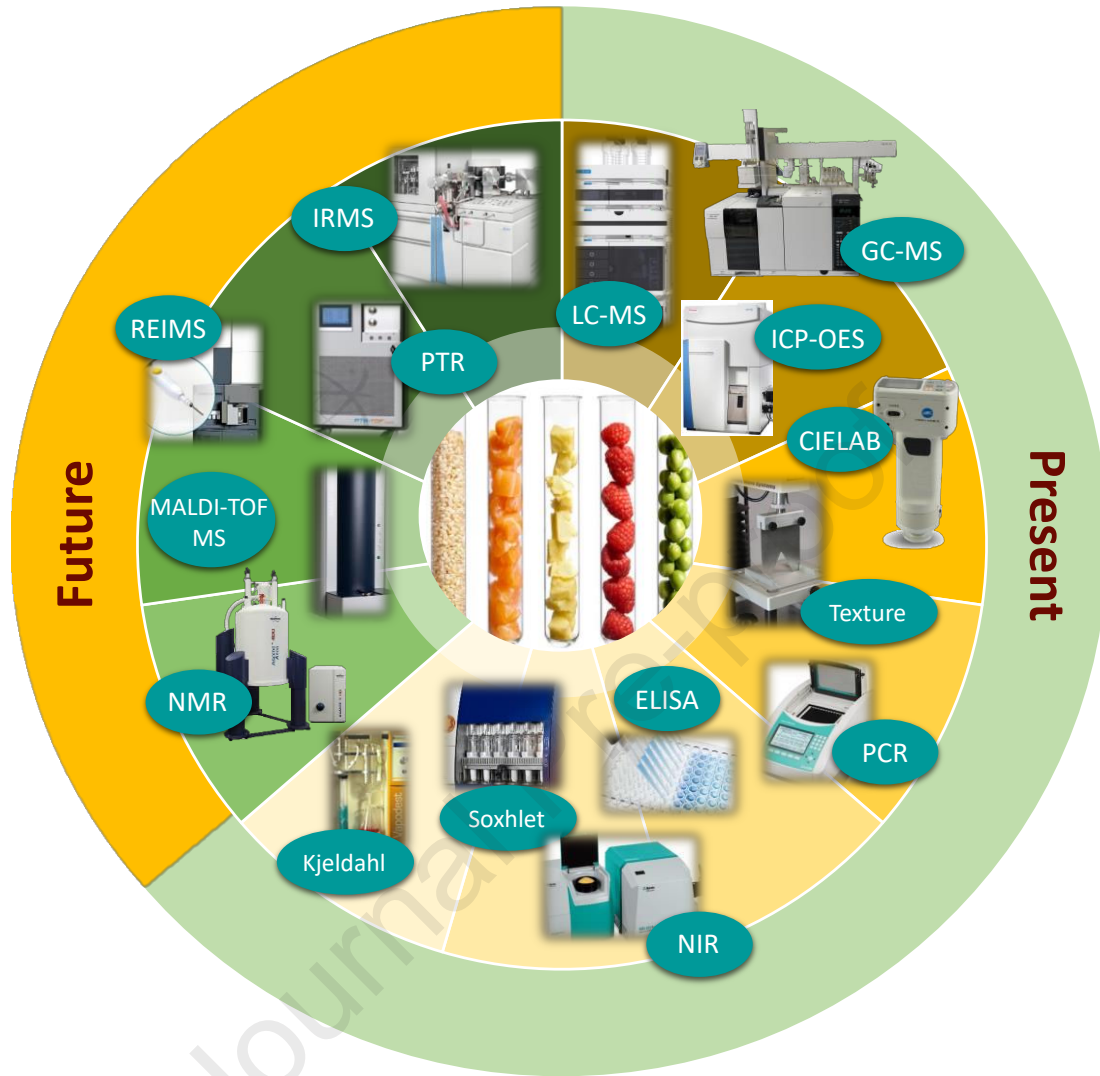
1372   **Fig. 1**

1373

1374

1375

1376

1377

1378

Autonomous robots

Simulation

Big Data analytics

Horizontal/vertical integration

FOOD QUALITY 4.0

Augmented reality

Industrial Internet of Things

1379

Fig. 2

1381

Stage 1
Organization strategy

Stage 2
Level of digitization of the
organization

Stage 3
The extent of digitization of supply
chain. Smart products and services

Stage 4
Employee adaptability with Industry
4.0

Stage 5
Top management involvement and
commitment

1382

1383   **Fig. 3**

1384

1385

1386

1387   **Fig. 4**

1388

1389

Fig. 5

HIGHLIGHTS

- Consumer interest in food quality call for advanced and reliable analytical methods

- Industry 4.0 has offered numerous opportunities in many fields, including food analysis.

- Food Quality 4.0 concept - determination of food quality using Industry 4.0 technologies

- AI, Big Data, and smart sensors are important enablers of Food Quality 4.0

- Innovations, digitalization, and automation experienced a massive boost

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal

relationships that could have appeared to influence the work reported in this paper.

2022-08-01

Food quality 4.0: From traditional approaches to digitalized automated analysis

Hassoun, Abdo

Elsevier