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# Food modelling strategies and approaches for knowledge transfer

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## Abstract

*Background* — Scientific software incorporates models that capture fundamental domain knowledge. This software is becoming increasingly more relevant as an instrument for food research. However, scientific software is currently hardly shared among and (re-)used by stakeholders in the food domain, which hampers effective dissemination of knowledge, i.e. knowledge transfer.

*Scope and approach* — This paper reviews selected approaches, best practices, hurdles and limitations regarding knowledge transfer via software and the mathematical models embedded in it to provide points of reference for the food community.

*Key findings and conclusions* — The paper focusses on three aspects. Firstly, the publication of digital objects on the web, which offers valorisation software as a scientific asset. Secondly, building transferrable software as way to share knowledge through collaboration with experts and stakeholders. Thirdly, developing food engineers' modelling skills through the use of food models and software in education and training.

## Keywords

scientific software, software re-use, modelling, model exchange, collaborative modelling, education

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# 44 1. Introduction

45 Knowledge transfer<sup>1</sup> based on models is a vital driver of scientific research and for putting  
46 research into practice. Particularly, the development of digital Information and Communication  
47 Technology (ICT) offers great opportunities to create interactive media that facilitates the  
48 communication for research partnerships (de Wit-de Vries et al., 2019). In food science, there is  
49 a growing interest in knowledge transfer among researchers and with stakeholders at large (e.g.  
50 industry, public institutions, consumers) (Thomopoulos et al., 2019; Erdogdu et al., 2017;  
51 Aceves Lara et al., 2018; Filter et al., 2015; Perrot et al., 2011; Plaza-Rodríguez et al., 2018).  
52 However, reviews show that the deployment of knowledge transfer by food scientists and food  
53 engineers is marginal (Djekic et al., 2019; Braun and Hadwiger, 2011). The inherent properties  
54 of food products and related processes (e.g. variability of raw materials, not fully formalized  
55 physics, heterogeneity of the structure) hamper knowledge transfer (e.g. Perrot et al., 2011). In  
56 food science, a major problem is the lack of *codifiability* (i.e. the ability to translate knowledge  
57 into symbols, such as equations and computer code), which expresses the degree of  
58 communicability and understandability of the domain knowledge. A computer code is an  
59 unambiguous codification of domain knowledge that can be readily shared, contrary to tacit  
60 (not encoded) knowledge. Moreover, food scientists that build mathematical models and  
61 software often lack the knowledge transfer expertise to make their work accessible to a larger  
62 audience. As a result, the (re-)use of scientific software in the food industry in Europe is limited  
63 and as such an outstanding challenge.

64 Software essentially captures expert knowledge formalised as equations (i.e. a mathematical  
65 model) and implemented as executable code (Davenport and Prusak, 2000). The hindrances to  
66 wider (re-)use of food research software are diverse, such as the lack of user-ready research  
67 software tools, the cost of getting acquainted with existing models, and the difficulty of  
68 designing adaptive reusable applications. Several papers address this knowledge transfer  
69 bottleneck. Datta and Halder (2008) and Saguy (2016) propose a road map for wider  
70 deployment of food models in industry. Datta (2016) discusses computer-aided food  
71 engineering to promote the use of virtualisation in the food industry. Perrot et al. (2011)  
72 describe opportunities offered by complex systems approaches to overcome limitations  
73 encountered by physics-based approaches. Della Valle et al. (2014) present prerequisites that  
74 favour the assimilation and the use of simple models in the baking industry. Plaza-Rodríguez et  
75 al. (2018) present a strategy for making a model publicly available and transfer predictive  
76 microbiology knowledge into operational applications. Haberbeck et al. (2018) present an open  
77 information exchange format for integrating and sharing knowledge captured in mathematical  
78 models in the food safety domain. Filter et al. (2015) present a strategy for developing expert-  
79 systems with broad end-user acceptance.

80 The food modelling community has a responsibility in strengthening the transfer of software  
81 conveying encoded domain knowledge, both, by making existing scientific software easier to  
82 find and (re)use, and by creating software that is easier to transfer to stakeholders. The former  
83 is a one-way<sup>2</sup> mechanism based on the dissemination of research results that requires post-  
84 treatment of the software (Plaza-Rodríguez et al., 2018). The latter is a bi-directional<sup>3</sup>  
85 mechanism that involves interaction between the modellers and the recipients of the software

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<sup>1</sup> See Battistella et al. (2016) for a review on technology and knowledge transfer.

<sup>2</sup> A *mechanism of output* according to Battistella et al. (2016).

<sup>3</sup> A *mechanism of process* according to Battistella et al. (2016).

86 and entails that the software meets certain requirements; for example, the production of  
87 outputs that are of interest to end-users (Datta and Halder, 2008).

88 To encourage knowledge transfer in the food domain, a comprehensive overview of knowledge  
89 transfer enabling methods, frameworks and approaches is needed. Our paper aims at initiating  
90 this overview. It adheres to the broad definition of knowledge transfer as the communication of  
91 thoughts, ideas, hypotheses, theories, etc. that alters the recipient's knowledge state<sup>4</sup> (Braun  
92 and Hadwiger, 2011).

93 This paper focuses on academia and industry as sources and recipients of knowledge related to  
94 food. It considers software and models as objects transferrable between stakeholders. The  
95 paper reviews transfer initiatives in food software and modelling, and discusses what the food  
96 community may learn and adopt from other scientific communities in terms of knowledge  
97 transfer strategies and approaches, and how this may benefit the food community. The paper is  
98 organized in four sections, each illustrating a different set of knowledge transfer mechanisms.  
99 Section 2 discusses ongoing efforts in knowledge transfer through physics-based models and  
100 phenomenological models embedded in software. Sections 3 & 4 present collaborative  
101 initiatives and strategies for building software that captures knowledge shared by specialists  
102 from different domains pertaining to a particular subject. Section 3 focuses on collaboration  
103 through software reuse, while section 4 discusses collaboration through shared understanding.  
104 Section 5 presents initiatives in education and training that promote modelling in food  
105 engineering curricula.

## 106 2. Knowledge transfer in food science modelling

107 The application of modelling techniques in the food domain is challenging due to intricate  
108 physical structures (e.g. foams, emulsions, suspensions, networks, gels), which are typically  
109 dynamic, undergo significant changes during manufacturing and exhibit varied behaviour  
110 during consumption (Mohammed et al., 2020). Food researchers in industry and academia  
111 increasingly produce mathematical models embedded in software that capture relevant  
112 knowledge of such phenomena. These models, referred as physics-based and phenomenological  
113 models, are potential vectors for Knowledge Transfer (KT) among researchers and with  
114 stakeholders at large. This section focusses on KT using such models.

### 115 2.1. Physics-based food science models

116 Physics-based modelling deploys a theoretical framework involving mathematical expressions  
117 of phenomena. When computed, a physics-based model generates virtually animated objects  
118 (evolving in time and space) that describe the considered system, matching observations  
119 (Saguy, 2016). These simulations result from analytical (i.e. exact) or numerical (i.e.  
120 approximate) models. Due to the complexity of food, the former has limited applicability for  
121 food products (Bimbenet et al., 2007). The latter, on the other hand, has much more deployment  
122 within the academic and industrial food community. There is a vast range of numerical  
123 techniques available including Finite Element Analysis (FEA), Discrete Element Methods (DEM),  
124 and Smoothed-Particle Hydrodynamics (SPH), which can be used to simulate a wide variety of  
125 phenomena involving solid and fluid-like materials.

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<sup>4</sup> Complies with the *frame of reference* in Battistella et al. (2016).

126 Numerical models have typically been deployed in three ways:

- 127 1. **Industrial manufacturing processes.** To determine and simulate important variables  
128 of process operation, e.g. the exit shape and the roll force of the torque for the rolling  
129 sheeting of dough (Chakrabarti-Bell et al., 2010; Chen et al., 2020). Another example is  
130 heat transfer modelling, which is probably the most common application of numerical  
131 techniques in food processing (Erdogdu et al., 2018), as the temperature of a product is  
132 critical for food safety and quality.
- 133 2. **Predicting complex phenomena.** To predict food breakdown during oral and gastric  
134 processes in humans (or pets) consider the interactions taking place in the oral cavity  
135 during the chewing for various food products (Harrison and Cleary 2014; Skamniotis et  
136 al., 2020). For example, the flow of a bolus resulting from the peristaltic waves inside a  
137 realistic stomach geometry (Ferrua et al., 2011) and food transport through the  
138 oesophagus during the swallowing of fluid food (Yang et al., 2007). The latter studied  
139 the effects of tissue properties, bolus properties (e.g. viscosity) as well as contraction  
140 and wave speed on the food transport process.
- 141 3. **Multiscale simulation design tool.** For linking the structure and behaviour of food in  
142 small scale processing to the bulk response of foods in larger scale processing.  
143 Multiscale numerical modelling is gaining importance in food science (Ho et al., 2013).  
144 For example, the texture of cereal solid foods can be predicted using FEA, by combining  
145 information about the product density (macro-scale), product cellular structure (meso-  
146 scale) and the mechanical properties of the constitutive materials (micro-scale)  
147 (Guessasma et al., 2011).

148  
149 Numerical models are of interest to the food industry as well as the non-food industry, e.g. for  
150 the design of innovative bio-based materials. However, KT based on these models is limited.  
151 Models often need to be re-engineered and adapted to specific problems, which requires  
152 technical skills from the user, and measurements of material properties. Additionally, there is  
153 the fear of sharing sensitive data, as well as budget and time constraints, which hamper  
154 corporate investments in a dedicated modelling service or department. As a result, the  
155 numerical models available in the scientific literature are hardly transferred beyond the  
156 community of modellers that developed them.

## 157 2.2. Phenomenological models: empirical & simplified

158 The development of phenomenological models from experimental results (also known as semi-  
159 empirical models) can be seen as a lightweight approach compared to the physics-based models  
160 discusses above. Phenomenological modelling sacrifices the mechanistic foundation and  
161 predictive power to provide pragmatic solutions to practical problems within time and budget  
162 constraints. Phenomenological modelling is common in food engineering and many models of  
163 this kind can be found in the literature (Baudrit et al., 2011).

164 Basic Knowledge Models (BKMs) are a specific type of phenomenological models that rely on  
165 statistical or machine learning techniques to cope with unknown aspects. They have three main  
166 characteristics that facilitate KT (Della Valle et al., 2014):

- 167 • **Relevant knowledge.** BKMs capture relevant knowledge about the mechanisms that  
168 change a product during a process. This principle ensures that the model conveys only  
169 knowledge about the food product or process that is relevant to users.
- 170 • **Use-property information.** BKMs provide information on the use properties of a  
171 product. Firstly, to be of value to the food sector, a BKM must model a system that is  
172 recognisable and of interest to potential users, such as process operators in the domain  
173 of food manufacturing (e.g. mixing, rolling, frying). Secondly, the BKM outputs should  
174 serve practical use (e.g. predicting product quality criteria).
- 175 • **Understandable and modifiable.** Using and modifying BKMs requires limited  
176 knowledge of mathematics and physics as BKMs use relatively simple equations.  
177 Additionally, modelling languages from the field of Artificial Intelligence, such as causal  
178 graphs, can make BKMs understandable to users that are not skilled modellers (Kansou  
179 et al., 2017; Baudrit et al., 2010). The main challenge is to separate the BKM's structure  
180 from its mathematical and implementation details.

181  
182 To further illustrate BKMs, consider the models describing a bacterial response to temperature,  
183 pH, and water activity. They associate a standard bacterial growth model, usually a sigmoidal  
184 model either a Gompertz or logistic (Zwietering et al., 1992) with thermal inactivation  
185 (Leguerinel et al., 2005), while the parameters are fitted to the data. Along the same lines,  
186 Romano et al., (2007) proposed a BKM that simulates the wheat dough expansion leavening  
187 process from the dose of yeast using Gompertz function and a linear-regression model. Kansou  
188 et al. (2013) extended this model by introducing a BKM for dough stability, using an exponential  
189 decay function. One can think of building a third BKM of dough expansion by coupling both  
190 models. This shows how phenomenological models can be reused and adapted to meet specific  
191 needs.

192 More elaborate BKMs integrate stochastic modelling to manage complexity, uncertainty and  
193 tacit knowledge (Perrot et al., 2011). Baudrit et al. (2010) present a Dynamical Bayesian  
194 Network (DBN) of cheese ripening that simulates the evolution of practical product properties  
195 such as odour, percentage of coating, and humidity. The DBN integrates a knowledge model of  
196 the microbial activity with imprecise information in the form of probability distributions  
197 learned from data. More precisely, the DBN is a causal graph whose nodes (variables) and edges  
198 (causal dependencies) represent the coupled dynamics of dominant microorganism growth  
199 with their substrate consumptions. With the help of experts in cheese ripening, the graph was  
200 built in such a way that it is explicit and understandable even for a person with modest or no  
201 modelling skills. Determining the conditional probability distributions, i.e. the parameters of the  
202 DBN, required a significant experimental effort and a large dataset to account for the kinetics. In  
203 return, the prediction accuracy of the model was rather high.

## 204 2.3. Transfer channels for scientific software

205 Mathematical models are valuable means of KT, particularly when formalised as scientific  
206 software, which ranges from a simple script written by a single researcher to an elaborate  
207 software package (e.g. modelling software) developed by several groups in a joint effort.  
208 Currently, the main routes for transferring scientific software to stakeholders in the food  
209 domain are:

- 210 1. scientific publication, with some information about the implementation of the model;

- 211 2. simulation results as required by clients, but without sharing the code that produces
- 212 these results;
- 213 3. software distribution via university or a university spin-off company; and
- 214 4. software hand-over to a company that handles the engineering and commercialisation.

215

216 These four routes basically reflect two approaches for sharing scientific software: (i) the  
217 academic approach, in which authors of the scientific software take care of the software use and  
218 dissemination (i.e. route 1 and 2), and (ii) the commercial and open-source approach, in which  
219 the software maintenance and the business aspects are entrusted to software specialists or a  
220 platform (i.e. 3 and 4). As food model developers are typically familiar with the academic  
221 approach, the next section focusses on the latter approach.

### 222 2.3.1. Hand-over scientific software to a development team

223 It can be beneficial to hand-over code to a software company, which then handles the software  
224 engineering tasks (e.g. user interface development, software development, maintenance, code  
225 testing, documentation) and the business aspects (e.g. licensing and distribution). Typical  
226 approaches for commercialisation are: (i) the development of fully integrated proprietary  
227 packages by a software company, (ii) proprietary packages set up for integration with external  
228 open-source packages, and (iii) the Independent Software Vendor (ISV) model, in which a  
229 software company offers a platform to ISVs (i.e. separate companies) that integrate their  
230 solutions in the platform (e.g. as packages) and offer it to their clients (e.g. ANSYS). ISVs are  
231 charged for the integration of their products in the platform, while they fully handle the  
232 development and the business aspects of their products (Goldbeck, 2017).

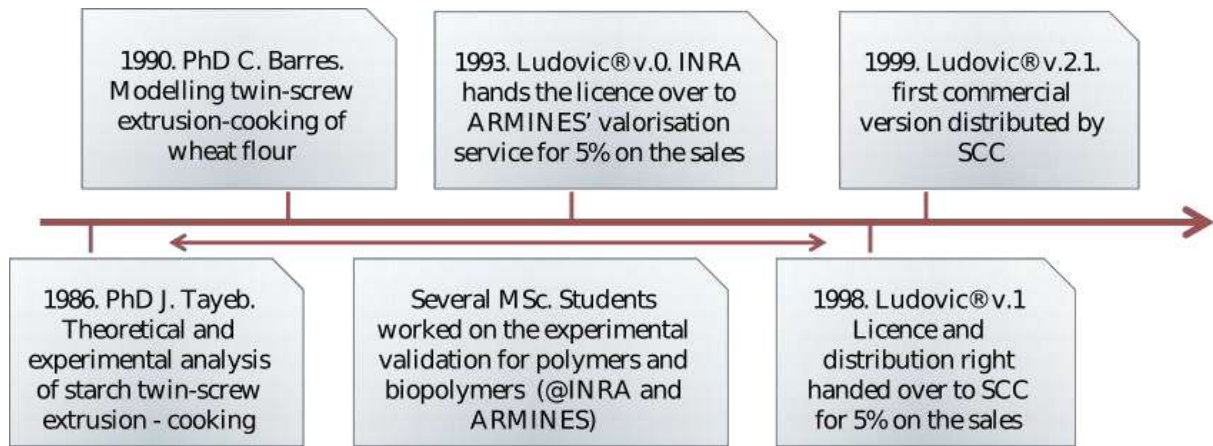
233 A primary market for scientific software commercialisation is research and development  
234 activities. In food, this concerns the development of innovative food products or packaging or  
235 the creation of new processes. Downstream in the R&D chain, scientific software can support  
236 product quality-assessment (e.g. safety risk, nutrition, conformity assessment), process  
237 optimisation and control, and supply chain or market trends analysis.

238 The Ludovic® case illustrates scientific software commercialisation. Ludovic® is a simulation  
239 software for the twin-screw extrusion of polymers and biopolymers developed and distributed  
240 by Sciences Computers Consultants (SCC)<sup>5</sup>. Twin screw extrusion has been developed in the 70's  
241 for various foods (e.g. snacks, breakfast cereals, infant flours, pet-foods). At that time, the  
242 approach to extrusion in industry was essentially empirical. In the eighties, the INRA and  
243 ARMINES institutes investigated theoretical and experimental aspects of the extrusion of  
244 starchy and other polymeric products. They developed a model based on continuum mechanics  
245 to rationalize the design of extruded starchy products (Della Valle et al., 1993; Vergnes et al.,  
246 1998). This model computed the temperature and the pressure profiles along the screw, as well  
247 as the Specific Mechanical Energy (SME). SME mainly determines the extent of the starch  
248 transformation and its viscosity, which in turn determines the product expansion at the outlet of  
249 the die. About six years after the model's main publication (1993), Ludovic® was released as  
250 the result of a business agreement between the two research institutes and SCC (Fig. 1). The  
251 initial model, written in FORTRAN, was given to SCC along with the Intellectual Property (IP)  
252 rights in return for a royalty on sales and free in house use of the software. SCC carried on the  
253 software engineering tasks (i.e. cleaning the code, developing a GUI, writing documentation,

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<sup>5</sup> <https://www.sccconsultants.com/en/ludovic-twin-screw-simulation-software.html>

254 with the help of the authors of the models to ensure scientific adequacy) and the distribution  
 255 and maintenance. Several companies use Ludovic®, which is now in its 6<sup>th</sup> version, at the early  
 256 stages of product design innovation and process optimisation to reduce the number of costly  
 257 trials. The research groups that initially contributed to Ludovic® have since been using the  
 258 commercial version in many research activities, for example to account for the texture  
 259 properties of extruded products.



260

261

**Figure 1.** Timeline illustrating the origin and development of Ludovic®.

262

### 2.3.2. CAE solutions, when end-users are modellers

263 Physics-based modelling and more specifically numerical modelling is generally used to create a  
 264 virtual space in which replications of products, processes or equipment are manipulated and  
 265 tested (i.e. Datta, 2016). Modelling, simulation, optimisation and dynamic studies are a part of a  
 266 wider scheme that is referred to as virtualisation (Marra, 2016). A number of manufacturing  
 267 sectors have invested in this approach, e.g. automotive, aerospace, packaging, and adhesives.  
 268 Virtualisation is used for product design and development; it offers an alternative to physical  
 269 trial-and-error exploration. In the food industry, the design of innovative products is one of the  
 270 applications that could benefit from this virtualisation approach (Saguy, 2016).

271 Numerical models can provide accurate predictions of the behaviour of a material under a  
 272 variety of boundary conditions, whilst conveniently highlighting important parameters of the  
 273 process analysed through parametric studies. Another advantage is that these models provide  
 274 results in an accessible format, such as colourful contour plots and explicit graphs, which enable  
 275 end-users to build a mental model of the phenomenon and subsequently use the knowledge  
 276 gained for product and process optimisation. Additionally, there are strong arguments for the  
 277 strategic importance of a wider use of virtualisation to support innovation in the food sector  
 278 (Saguy, 2016).

279 The preferred KT channel for this type of model is commercial Computer-Aided Engineering  
 280 (CAE), i.e. a software that assists end-users in the process of developing their own numerical  
 281 models. The growing interest for such computational models has been driven by the increase in  
 282 available processing power as well as the multiplication of commercially available software  
 283 packages dedicated to materials and chemical processing (e.g. Comsol<sup>6</sup>, ANSYS<sup>7</sup>). These  
 284 commercial solutions are typically accompanied by technical manuals, training, free student

<sup>6</sup> <http://www.comsol.com/products>

<sup>7</sup> <https://www.ansys.com/solutions/solutions-by-industry/materials-and-chemical-processing>

285 download licenses and customer support. OpenFOAM<sup>8</sup> is an example of an open-source  
286 software under the General Public Licence (GPL). GPL allows for free use, modification and  
287 redistribution. In chemical engineering, one can find easy-to-use CAE tools for simulating  
288 processes in the energy, gas, chemical, petroleum and pharmaceutical industry (e.g. ProSim<sup>9</sup>).

289 In the food domain, CAE tools offer great assistance for tasks that can be partially automated  
290 such as processing (solving equations), post-processing and coding. However, current CAE  
291 solutions are unlikely to efficiently assist the modelling of solid food products (i.e. writing  
292 mathematical expressions that capture the physical system, Datta., 2016). Problem formulation  
293 requires good modelling skills and good knowledge of food physics and experiments. In the food  
294 domain, this evidently limits the pool of potential end-users. Hence, in the food industry the  
295 application of physics-based modelling is currently conducted by in-house modellers in big  
296 companies, specialist software companies or academic research groups.

297 Datta (2016) proposes two paths to increase the utility of CAE in the food domain: (i) the design  
298 of a set of modelling frameworks that address food processing, quality and safety, and (ii) an  
299 increased use of CAE tools and virtualisation in education, as this is happening already in some  
300 university engineering courses. It is also possible to take advantage of the emerging cloud-based  
301 technologies that have transformed many industries. It has been argued that running numerical  
302 simulations of manufacturing processes on cloud-based platforms could foster a collaborative  
303 research environment whilst providing means for research digitalisation and knowledge  
304 sharing as well as saving on local computational and data storage resources (Yang et al., 2019).  
305 This could be a future trend that would facilitate the optimisation and exploitation of advanced  
306 mathematical modelling tools by stakeholders.

## 307 2.4. Limitations of current diffusion channels

308 Current channels for KT with scientific software are limited. Scientific papers generally contain  
309 minimal descriptions of the implementation, and even when the code is available, using it  
310 effectively requires a serious amount of additional work (Gil et al., 2016). The lack of an  
311 harmonized exchange format is particularly limiting, as it is well known that being able to  
312 integrate, question and challenge new knowledge is essential for perceiving and accepting its  
313 added value (Drechsler et al., 2016). Challenges with software commercialisation are the  
314 intensity and duration of the procedure. Only a few scientific software vendors are interested,  
315 leaving most of the scientific software of a domain aside. Developing CAE solutions dedicated to  
316 the food domain would be beneficial for KT, in particular because it would enable the receiving  
317 agent to build their own models, reusing components developed by others. For now, this  
318 channel has a relatively small user base in the food sector, although it is expected to grow with  
319 the development of commercial software (Saguy, 2016). Still, the CAE tools favour certain types  
320 of modelling and require suitable training, as such, they are unlikely to offer a generic solution  
321 for transferring scientific software.

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<sup>8</sup> <https://www.openfoam.com>

<sup>9</sup> <http://www.prosim.net/en/index.php>

## 322 3. Towards reusable scientific software

323 In Europe, guidelines have been issued to incite scientists to adopt development practices that  
324 will make their software reusable (Chue Hong, 2014, Fehr et al., 2019). Additionally, sharing  
325 research data is well established as a key aspect of open science, which is expected to accelerate  
326 innovation in industry. It is typically realised using the European Commission’s program  
327 European Open Science Cloud<sup>10</sup> that implements the FAIR<sup>11</sup> principles (i.e. Findability,  
328 Accessibility, Interoperability, and Reusability), as well as related developments on (research)  
329 data management plans and domain protocols to share data. This section reports on initiatives  
330 that could encourage the reuse of scientific software in the food domain.

### 331 3.1. Information to accompany scientific software

332 There are several proposals like the Science Code Manifesto<sup>12</sup> aiming at paving the path toward  
333 reusable scientific software (Chue-Hong, 2014). Among them, “Software Engineering at Google”  
334 (Henderson, 2017) illustrates a gold standard that is unrealistic for academics, yet some of the  
335 good practices, frameworks and tools presented could inspire the scientific community. The  
336 DLR (German Aerospace Center) Software Engineering Guidelines (Schlauch et al., 2018) are an  
337 interesting example of top-down recommendations aiming at supporting scientists in improving  
338 the reusability of their software. Another framework for informing about scientific software is  
339 proposed by Fehr et al. (2019). It defines a list of requirements for academic software, typically  
340 pieces of code written by a PhD student, to support the hand-over to the other scientists (in the  
341 group) and the continuation of the project. Another approach for evaluating scientific software  
342 in the food domain could be to tailor the Technology Readiness Level (TRL) methodology to  
343 food science (Altunok and Cakmak, 2010; Armstrong, 2010).

344 The multi-level framework for scientific software reuse (Chue-Hong, 2014), is a good starting  
345 point for scientists new to this topic. This framework associates end-user benefits with four  
346 software information levels that support a researcher in the process of providing information  
347 about the software, such that a developer can gradually improve the reusability of the software.  
348 The proposed four levels are:

- 349 ● L1 (Absolute Minimum): requirements that put no barrier on the developer. Should be  
350 considered basic requirements for any researcher that publishes results from a self-  
351 developed software.
- 352 ● L2 (Useful Minimum): additional effort to support at least the own use of the software.
- 353 ● L3 (Pragmatic Minimum): a desired (according to Chue-Hong, 2014) standard level of  
354 information that supports the collaboration with external developers.
- 355 ● L4 (Good Minimum): actively encourages software reuse through the adoption of  
356 essential software engineering techniques.

357  
358 For each level, the requirements are classified in categories. **Table 1** shows the requirements  
359 for L1. As scientific editors get increasingly concerned with the traceability of research results,  
360 requirements of this kind might become mandatory for submission to peer-reviewed journals,  
361 as soon as a new scientific software is involved. Notice that, this framework is sufficient to

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<sup>10</sup> <https://www.eosc-portal.eu/about/eosc>

<sup>11</sup> <https://www.go-fair.org/fair-principles/>

<sup>12</sup> <http://sciencecodemanifesto.org/>

362 support the editing of basic metadata (information describing the software) and the creation of  
 363 accompanying files. Some of these metadata are required for depositing software into a digital  
 364 repository for archiving and referencing (e.g. Jackson, 2018). Where dealing with copyright and  
 365 licensing aspects, which is part of the process, can be troublesome, the REUSE<sup>13</sup> website offers  
 366 useful support in this regard.

367

368 **Table 1.** Level 1 requirements for informing on software reuse (Chue-Hong, 2014).

Category	L1. Absolute Minimum
License (legal information about the software reuse)	“the software has a license that allows for reuse (this can include non-Open Source licenses...under academic or commercial terms)”
Availability (where and how to get access to the software)	“the software has been published somewhere such that people can find it (this could be as a tar archive on a website)”
Quality (functional and non-functional requirements)	“the software has some minimal indication of what it is supposed to do... normally as part of a README”
Support (ways to contact the developer in charge of support)	“the software indicates some way of contacting the original/current developer (instead of good documentation), normally as part of a README”
Incentive (how to acknowledge the software development)	None (starts at level 2)

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### 370 3.2. Infrastructures for reuse of scientific software

371 Sustainable scientific software reuse should be based on a suitable infrastructure for storing,  
 372 archiving and making the code accessible. Therefore, authors must deposit their software  
 373 alongside other files (e.g. README, RUNME) into digital repositories and fill in registry forms  
 374 that allow for curation by other users. Jackson (2018) offers useful recommendations for the  
 375 deposit of software, such as the delivery of a persistent digital identifier (e.g. Digital Object  
 376 Identifier, DOI) that assures that the software can be cited and that the author gets credited for  
 377 the work. Notice that, general purpose code repositories, such a Github, do not automatically  
 378 provide persistent identifiers, although mitigating procedures exist<sup>14</sup>. Certain repositories are  
 379 recommended for specific developer communities. For instance, CRAN<sup>15</sup> is well-known among  
 380 users of R<sup>16</sup> as the repository that stores R packages with their documentation. Similarly, SciPy<sup>17</sup>  
 381 is well known among Python<sup>18</sup> users. For any scientific software, it is important to consider  
 382 archiving and referencing the software via registry services alongside the deposit of the code. In  
 383 fact, registration and indexation might be more important for a scientific community than the  
 384 code repository hosting service itself (Gil et al., 2016). General purpose digital repositories, such  
 385 as FigShare and Zenodo, can be used for registering and archiving software (as for any other  
 386 research products) and for making its title, DOI and licence citable (Jackson, 2018). Finally,

<sup>13</sup> <https://reuse.software/>

<sup>14</sup> <https://guides.github.com/activities/citable-code/>

<sup>15</sup> <https://cran.r-project.org/>

<sup>16</sup> <https://www.r-project.org/>

<sup>17</sup> <https://www.scipy.org/>

<sup>18</sup> <https://www.python.org/>

387 Software Heritage<sup>19</sup> is a recent international initiative that offers a service for indexing,  
388 organizing, making referenceable and accessible all the software that conveys technical and  
389 scientific knowledge. Software Heritage archives and assigns an intrinsic and persistent  
390 identifier for digital objects (i.e. swh-id).

391 One can also find domain-specific software repositories, driven by a community of scientists for  
392 collecting food safety models in their field, such as the Risk Assessment and Knowledge  
393 Integration Platform (RAKIP)<sup>20</sup> (Plaza-Rodriguez et al., 2018; de Alba Aparicio et al., 2018). They  
394 enable scientists to register their software via a set of metadata that capture relevant  
395 information for the domain. Interestingly, some of these repositories require compliance with a  
396 common modelling framework to favour data exchange between various modelling tools and  
397 the coupling of models in general (Gil et al., 2016).

398 FSL-Lab is a graphical modelling platform for the integration of risk assessment models that  
399 goes a step further in term of model reusability (de Alba Aparicio et al., 2018). One of the FSK-  
400 Lab key features is the support of a markup language for script-based or application-based  
401 models (Food Safety Knowledge Markup Language, FSK-ML), that is used to annotate models  
402 with metadata. FSK-ML allows for a harmonized writing and reading of mathematical models  
403 regardless of their sources, which facilitates greatly their integration and re-use in FSK-Lab.  
404 FSK-ML is expected to become a format for exchange of information broadly adopted by the  
405 microbial food safety community (i.e. regulatory agencies, food industries, consultancy  
406 companies, and food scientists) in order to facilitate the reusability of scientific models to  
407 improve risk assessment and decision making by food safety managers (Haberbeck et al., 2018).

408 Software deposit solutions capture metadata about the software, but sometimes in an  
409 unstructured way, e.g. as text in a README file. Additionally, the documentation provided in  
410 code repositories mostly focuses on the installation process (Gil et al., 2016). This makes it  
411 difficult for potential end-users to find software that matches their needs. Having the metadata  
412 captured in a software registry linked to the code makes the software searchable, discoverable  
413 and re-usable. This is an essential aspect of software sharing that can be addressed with  
414 software ontologies (i.e. controlled vocabularies that specify information about a software). The  
415 OntoSoft ontology (Gil et al., 2015) is an example of a general software ontology centred on  
416 scientific software sharing. OntoSoft<sup>21</sup> captures six information items that can be queried by a  
417 user (Gil et al., 2015): identifying the software, understanding and assessing software, executing  
418 the software, getting support, doing research, and updating. This ontology is at the core of a  
419 distributed software registry that offers a way to register and discover scientific software.

### 420 3.3. Barriers for scientific software reuse

421 The publication of datasets and software is a growing trend that is likely to become even more  
422 pronounced in the near future. This trend is encouraged by scientific publishers, funding  
423 agencies and research organisms that promote open science. Despite this, there is a risk that a  
424 great deal of datasets and software currently developed by researchers in food science remain  
425 unpublished and inaccessible to potential users.

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<sup>19</sup> <https://www.softwareheritage.org/>

<sup>20</sup> <https://foodrisklabs.bfr.bund.de/rakip-model-repository-web-services/>

<sup>21</sup> <https://www.ontosoft.org/index.html>

426 Main explanations for the limited adoption of practices that favour software reuse reported in  
427 other domains (e.g. Gil et al., 2016) also apply to the food modelling community. They can be  
428 summarised into three categories, lack of credit, lack of knowledge, lack of suitable “ecosystem”,  
429 e.g. guidelines and tools. Traditionally, food science does not rely heavily on programming,  
430 therefore the lack of knowledge about practices and tools that favour software reuse is natural.

431 Similarly, while developing an infrastructure to share food science models might be highly  
432 beneficial, the community lacks a format for describing simulation models (Plaza-Rodriguez et  
433 al., 2015). However, the lack of credit is probably the most critical bottleneck for a large  
434 diffusion of food science models. In science, there is a major imbalance between the effort  
435 invested in coding, documenting, maintaining and publishing the code, and the credits/benefits  
436 that the author can get from it (Chawla, 2016). Initiatives from publishers and communities to  
437 measure the impact of a scientific code are currently tackling this imbalance and will probably  
438 continue alongside the evolution of scientific publications, see for example the software citation  
439 guide (Katz et al., 2021) and the CODECHECK system (Nüst and Eglén, 2021).

#### 440 4. Collaboration through shared representations

441 The code developed by researchers in the process of scientific discovery should be shared with  
442 the scientific community, like a research paper or a dataset. However, the primary goal behind  
443 the development of scientific code is generally not knowledge transfer. This section focuses on  
444 collaborative modelling techniques that aim at creating software usable by people other than  
445 scientists.

446 Collaborating with other scientists, domain experts, stakeholders or even consumers, is not  
447 uncommon in the food sector. In general, the need to integrate expertise from various domains  
448 grows with the system scale and its complexity (van Mil et al., 2014). For instance, modelling the  
449 proofing of wheat dough – i.e. the first fermentation operation of the bread-making process –  
450 needs only knowledge of the dough rheology and of the leavening agent activity. However, a  
451 bakery will probably find modelling the whole bread-making process more useful, which  
452 includes, in addition to the knowledge of the physics of the dough, the assessment of the quality  
453 of the flour and the prediction of the sensory properties of the bread; both aspects demand  
454 domain expertise and are not fully tractable with the current state-of-the-art. Collaborating  
455 actively with industry and civil society is a way to improve the relevance of software beyond the  
456 scientific community (Sein et al., 2011).

457 However, where integrating different views of the same system is expected to promote  
458 understandability and (re)usability by a diverse audience, working with non-modeller  
459 contributors is challenging and calls for specific methods and tools. Potential mechanisms that  
460 facilitate collaboration can be found in the knowledge engineering domain. This field includes  
461 the acquisition of knowledge from domain experts, participative modelling and the  
462 development of controlled vocabularies (e.g. ontologies). This section reports on collaborative  
463 modelling initiatives in the food domain, such as the development of standardized food-related  
464 ontologies and the crowdsourcing of food data.

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## 4.1. Involving domain experts in creating food software

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Involving experts in the creation of software, while keeping these experts away from low-level implementation details, is a prerequisite in the field of knowledge engineering and the development of Knowledge-Based Systems (KBS). KBSs designate a class of software systems (including expert systems and decision-support systems) that implements an automated knowledge source that can be consulted by users to generate valuable results (e.g. complex question answering or supporting decision-making). A KBS generally collates information from different sources, such as domain specialists, literature, and web resources (Aussenac-Gilles and Gandon, 2013). Basic principles of acquiring knowledge from experts include (Schreiber et al., 2000): (i) building a shared representation of the domain knowledge sufficient for fulfilling the goal of the software, (ii) focusing on capturing the conceptual structure of the knowledge (i.e. the so-called knowledge-level), leaving aside programming considerations, and (iii) adopting iterative and incremental development of the software.

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Not many papers have addressed this topic in the context of food. Ndiaye et al. (2009) discusses the creation of a KBS for bread-making that captures the reasoning of bread technologists. Additionally, an incremental modelling approach is proposed to spur experts in providing feedback and informative critiques on the model structure (Kansou et al. 2014). Thomopoulos et al. (2013) presents an approach for learning interpretable data-driven models, which was applied to the processing and qualities of cereal foods. They used a domain ontology to select the factors from the dataset (e.g. cooking temperature) that would most likely affect the quality of the products (e.g. vitamin content). Subsequently, they derived decision trees from the data. The experts' feedback on the resulting decision trees were used to enrich the ontology, starting a new cycle, until the experts required no further improvements. In the same vein, the Food Informatics project (Koenderink et al., 2005) developed an approach for supervised construction of food ontologies, in which food experts had to select relevant concepts and properties (relations) within a set curated automatically from web resources.

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Eliciting knowledge about food is often delicate when know-how and sensory criteria are involved, because it often involves tacit knowledge that is difficult to put into words. To describe the human evaluation of an ongoing food process, Curt et al. (2004) adapted an observer-trainee technique combining explanation steps, interviews and concrete practical sessions. The principle was to have an expert practitioner, such as a product manager, explain and train a "trainee" (e.g. the modeller) which led to the identification of the indicators (e.g. colour, stickiness, particle size, etc.) and their attributes (e.g. definition, operating conditions, measurement scales, location in the process, etc.). This approach was adapted by Sicard et al. (2011) for monitoring cheese ripening controlled by the cheesemakers in order to develop a Dynamic Bayesian Network (DBN) of this operation (see section 2.2). The knowledge elicitation was carried out as follows. The first phase captured operational know-how about the cheese ripening process with the aim of building an operational representation of the indicators and of the decision rules used by the operators to control the process. In a second phase, food scientists enriched this operational representation with concepts and relations describing the microbiological and biochemical phenomena. The result was an integrated probabilistic model that was able to predict the indicators of the different phases of cheese ripening.

## 507 4.2. Participative modelling

508 Addressing societal issues, the collaborative and integrative aspects of modelling are even more  
509 important. Issues addressed at the food system level, especially those involving food security or  
510 sustainable production, are complex as they involve several dimensions and stakeholders with  
511 different visions of the system (van Mil et al., 2014) and potential conflicts of interest. This  
512 requires an appropriate methodology for reconciling these visions and determining the  
513 interventions that would most likely be accepted by the actors, and hence most likely succeed.  
514 This asks for participatory approaches that support decision-making in a multi-actor context  
515 (e.g. using risk-benefit analysis and multi-criteria decision, Bana E Costa, 2001), involving  
516 experts from different disciplines (e.g. agronomy, nutrition, environment) and various  
517 stakeholders (e.g. consumers, food producers, public authorities, technical centres) in the  
518 decision process that reconciles their different points of view (Joerin et al., 2009).

519 More specifically, participatory modelling involves the actors in the creation of models that will  
520 ultimately facilitate the decisions. The field of resource and environmental management is  
521 particularly active in participatory modelling (Voinov et al., 2016). Noteworthy developments in  
522 the field of participatory modelling address modelling aspects of the actors' dialogue related to  
523 the sustainability of food systems. For example, semi-automated argumentative approaches  
524 based on Dung's model (1995) allow for formalising arguments and contradictions, analysing  
525 conflicts of interest and helping to solve polemics. Thomopoulos et al. (2015) developed a KBS  
526 for re-thinking the agri-food chain's organisation with nutritional, safety and organoleptic  
527 recommendation arguments. Bisquert et al. (2017) present a multi-criteria computational  
528 cognitive model for argument acceptance (applied to the selection of durum wheat) informed  
529 with actor arguments, associations and opinions about food product (e.g. pasta, semolina)  
530 quality and life-cycle assessment criteria (e.g. dependence to chemical inputs). With the growing  
531 concern regarding the sustainability of the food systems, research projects including  
532 participatory modelling are bound to gain importance in the near future.

## 533 4.3. Crowdsourcing

534 Collaboration with experts or stakeholders is based on information exchange, during many  
535 meetings, either face-to-face, over the phone or through videoconferencing. This approach  
536 favours the elicitation of expertise and non-trivial positions on a subject, but it also hampers the  
537 involvement of a large number of contributors from different places, hence it allows only for the  
538 creation of small scale KBSs. As web-based services become increasingly sophisticated and  
539 powerful, it is possible to collect and integrate inputs from a large number of people across the  
540 world, aiming at larger scale applications. Consequently, web technologies and crowdsourcing  
541 are expected to play a bigger role in participatory modelling in the near future (Voinov et al.,  
542 2016). Several web applications to collaboratively build a model are already available, such as  
543 ArguBlogging, an application that automatically formalises and structures dialogues posted on a  
544 web platform as a computable model (Bex et al., 2014). Kurtz et al. (2021) propose an AI  
545 approach, based on the concept of collective attitude, to analyse a large-scale survey on  
546 consumers' perception of food, while Taillandier et al. (2021) mix arguments from web debates  
547 and agent-based modelling to simulate opinion diffusion on vegetarian diets.

548 Because food concerns everyone, food issues **can spark the interest** of many internet users that  
549 could provide information about their consumption or about their preferences. Open Food

550 Facts<sup>22</sup> epitomizes the successful application of crowdsourcing in the food sector. The  
551 contributors (>1800) scan the information given on the product package (e.g. nutritional facts,  
552 allergens, ingredient list, barcodes) and send it to a server via a smartphone application. The  
553 data collected so far covers more than 75000 products from 150 countries and is available to  
554 the public as open data. Open Food Facts conveys massive volumes of basic information about  
555 commercial food products to a large audience. Notice that, the community driven FSMR  
556 discussed above also relies on the internet to promote reuse of the scientific models and  
557 simulation tools developed by the food safety modelling community in academia, the food  
558 industry and public institutions. The crowdsourcing strategy assumes the creation of an open  
559 repository of models and the development of standardized information exchange formats. As a  
560 proof of concept, a web-based model repository has been implemented using a Google based  
561 infrastructure<sup>23</sup> to inventory existing food safety models (Filter et al., 2016).

## 562 4.4. Standardized food-related ontologies

563 Collecting and structuring information about a relevant part of the world and disseminating this  
564 information such that it can be shared with others is a fundamental aspect of KT. An ontology is  
565 defined as an explicit and formal specification of a shared conceptualisation (i.e. a mental  
566 model) of an aspect of reality (i.e. the domain) (Ushold & Gruninger, 2004). It has a structuring  
567 orientation that can help researchers, professionals and citizens to formalise and share  
568 expertise in such a way that it can be processed by both humans and computers (Roa et al.,  
569 2014).

570 As a Semantic Web technology, ontologies promote the semantic interoperability between  
571 information from different sources, which limits ambiguity and extends the scope of data  
572 available for querying by capturing the intended semantics of data (Shadbolt, 2006). Ontologies  
573 can be formally specified in specialised languages, such as the RDF Schema and OWL web-  
574 standards, which are lightweight knowledge representation languages, in which inferences can  
575 be derived from existing information (Krötzsch, 2012). Many formal ontologies are freely  
576 available on dedicated portals (e.g. Bioportal<sup>24</sup>, Agroportal<sup>25</sup>, Ontology Lookup Service<sup>26</sup>), some  
577 provide directly valuable resources to professionals (e.g. Gene Ontology<sup>27</sup>), but most of them are  
578 used to annotate information exchange between human agents and/or machines (Roa et al.,  
579 2014).

580 In food science, there are several publicly available ontologies, many of them focussing on a  
581 specific product (e.g. wine, pizza, beer). Boulos et al. (2015) review larger scope ontologies such  
582 as FOODS, AGROVOC<sup>28</sup>, FoodOn<sup>29</sup>, Open Food Facts<sup>30</sup>. However, not many can be seen as  
583 conclusive realisations of KT from the food science community because the focus is often on the  
584 non-technological aspects of food such as safety, food security, disease or health profile,  
585 nutritional facts, and supply chain elements. This can be illustrated with FoodOn (Dooley et al.,

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<sup>22</sup> <https://world.openfoodfacts.org>

<sup>23</sup> <https://sites.google.com/site/openfsmr/>

<sup>24</sup> <https://bioportal.bioontology.org/ontologies>

<sup>25</sup> <http://agroportal.lirmm.fr>

<sup>26</sup> <https://www.ebi.ac.uk/ols/index>

<sup>27</sup> <http://www.geneontology.org>

<sup>28</sup> <http://aims.fao.org/vest-registry/vocabularies/agrovoc>

<sup>29</sup> <https://foodon.org/>

<sup>30</sup> <https://world.openfoodfacts.org/>

586 2018), which was initially built to be used in collaboration with Genomic Epidemiology  
587 Ontology (GenEpiO<sup>31</sup>) to specify foodborne disease risks and not food science or technology.  
588 AGROVOC, on the other hand, is a generic multilingual thesaurus developed by the Food and  
589 Agriculture Organisation (FAO) with direct interest for KT and covering many fields in  
590 agriculture and food (Caracciolo et al., 2013).

## 591 4.5. The way forward

592 Open-source and **open access** software and data are becoming the norm in research. From this,  
593 we may infer that the trend towards KT is about to accelerate. A breakthrough in the annotation  
594 of food-related data with ontologies as a standard practice is needed to unleash the power of  
595 data networks (i.e. the value of an individual information item increases with the size of the  
596 data-pool it is associated with) (De Leenheer and Christiaens, 2018). This data network is a  
597 priority for the community working on vocabularies and ontologies in the field of food and  
598 agriculture. Agroportal already offers services to store, handle and display the mappings (or  
599 alignments) between ontologies; these mappings can be either uploaded or automatically  
600 inferred when classes share common properties (Jonquet et al., 2018).

601 A concern regarding the evolution towards openness is the intellectual property and data  
602 protection. The community should strive to avoid data-monopolies, as they lead to an unfair  
603 distribution of the wealth generated from data (Mazzucato, 2008) and protect contextual  
604 integrity, which should help preserve privacy and competitive advantage in data-sharing  
605 environments (Nissenbaum, 2009). The open-source initiative<sup>32</sup> provides resources for further  
606 insight.

## 607 5. Education and training

608 A considerable number of well-established European universities offer curricula addressing food  
609 science and technology, typically focussing on food engineering, microbiology and supply chain  
610 management. Several educational programs teach food modelling through learning-by-doing  
611 using general-purpose tools such as Matlab or Comsol. However, few institutions seem to put  
612 significant emphasis on advanced modelling and simulation techniques and scientific software  
613 in general. The availability of web-based course material appears also to be sparse. Instruments  
614 such as Massive Open Online Course (MOOCs) and Small Private Online Courses (SPOCs) have  
615 the potential to expand KT on to a large audience, while these can also be deployed to educate  
616 and train professionals. Below, three initiatives that illustrate this potential are highlighted.

617 In 2014, a special interest group of the ISEKI Food Association (IFA) started the International  
618 School on Modelling and Simulation in Food and Bio Processes (MSFS), which applies a short-  
619 term intensive training format. The Cost Action CA15118, FoodMC<sup>33</sup>, chose this school as its  
620 training school and over 100 scholars, coming from all over the world, have attended it so far.  
621 To the best of our knowledge, it is the only attempt to create a transversal community in which  
622 food engineers, food technologists and food scientists improve their modelling skills, interacting  
623 with each other and embracing the power of numerical techniques and tools for design and

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<sup>31</sup> <https://genepio.org/>

<sup>32</sup> <https://opensource.org>

<sup>33</sup> <https://www6.inrae.fr/foodmc>

624 innovation in the food sector. Datta (2016) agrees that the development of human resources is  
625 important to favour a generalised use of modelling tool in the food industry and KT. Yet, there is  
626 a relatively small and geographically dispersed student population eager to acquire the required  
627 skills. Therefore, the deployment of MOOCs for an international audience would allow for  
628 increasing the global outreach of existing and future initiatives.

629 Physics-based simulators when embedded in virtual tools could be an excellent medium to  
630 support KT and training in the food domain. Singh and Erdogdu (2009) developed a set of  
631 interactive computer simulations of food processing operations for students to conduct basic  
632 virtual experiments, along with a website that offers the resources<sup>34</sup>. Each of their 23 virtual  
633 experiments offers contextual information (e.g. industrial procedure, link to related-information  
634 on the internet), theory and data analysis information, a description of the experimental  
635 procedure and a simulator that mimics the actual experiment and allows for changing its setup  
636 by changing input parameters. Similarly, FEPSIM<sup>35</sup> provides a free web-based education tool  
637 that offers various physics-based modules (built on Matlab and ANSYS CFX/FLUENT) related to  
638 food engineering (Koulouris et al., 2015).

639 MESTRAL<sup>36</sup> is another example of pedagogical material based on simulators enriched with  
640 related information (Suciu et al., 2021). MESTRAL converted actual research results into  
641 educational materials and is currently available for master and PhD students in food  
642 engineering. The online repository contains 15 modules. Each module is built along the same  
643 conceptual framework that includes a *(i)* simulator (that re-uses scientific software from  
644 previous research), *(ii)* contextual information, and *(iii)* background knowledge both captured  
645 in standardized conceptual maps (Cmaps, Novak & Gowin, 1984) and in “knowledge sheets”. A  
646 Cmap is a knowledge modelling technique using diagrams that represent semantic relationships  
647 between concepts. Each Cmap in MESTRAL respects a template (i.e. meta-model) that imposes a  
648 tree-like organisation, a type of concept and a limitation on the number of concepts, to facilitate  
649 assimilation of the content. The digital material is composed of hypermedia that embed links  
650 from Cmaps towards *(i)* other Cmaps or the simulator, *(ii)* knowledge sheets that contain text,  
651 photos or videos, and *(iii)* external resources via URLs. The simulators run simulations based on  
652 case-study datasets that the user can display at will using sliders and plots.

## 653 6. Conclusion

654 This review paper illustrates the challenge of KT in food science through *(i)* a discussion on  
655 existing and emerging dissemination channels and *(ii)* arguing the need for an increased  
656 collaboration when building food-oriented software. Section 2 discusses the channels for  
657 physics-based models and phenomenological models embedded in software. Physics-based  
658 models are often transferred to end-users following a learning-by-doing strategy. This strategy  
659 can be improved by the development of adequate Computer-Aided-Engineering solutions and  
660 by a stronger emphasis on modelling in food science education programmes. For  
661 phenomenological models, the traditional diffusion channels for scientific models (i.e. scientific

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<sup>34</sup> <http://rpaulsingh.com/learning/virtual/virtual.html>

<sup>35</sup> <http://fepsim.food.teithe.gr/fepsim/default.aspx>

<sup>36</sup> <https://lms.agreenium.fr/course/index.php?categoryid=27>

662 publication) insufficiently support the reuse of the scientific software by a large audience even  
663 though the Ludovic® example shows that KT can be fruitful for both academia and industry.

664 Section 3 argues that new diffusion channels relying on web-based technologies develop rapidly  
665 and become increasingly relevant for KT. Most promising solutions provide tools for archiving,  
666 annotating, querying and publishing software, so as to give any user access to the necessary  
667 materials and accompanying information regarding a software (e.g. metadata, documents,  
668 running example) and also give credit to the authors.

669 Section 4 reviews the idea that building scientific software from shared knowledge can facilitate  
670 KT between miscellaneous stakeholders, including experts and practitioners, in an iterative  
671 process. It may even allow for encoding tacit (i.e. unarticulated) knowledge. Collaborative  
672 modelling takes this a step further by supporting a multi-user context, while web-based  
673 technologies allow for involving a physically dispersed community.

674 Section 5 notes that the scarcity of modelling skills amongst food engineers currently hampers  
675 successful KT. Several educational programs now teach food modelling through learning-by-  
676 doing strategies. In parallel, a few resources for teaching modelling online have been developed  
677 by food scientists. However, offering online, easily accessible and high-quality educational  
678 material is still an outstanding challenge in the food domain.

679 By highlighting miscellaneous approaches regarding scientific software, this paper aims at  
680 promoting KT between and within academia, industry and other stakeholders, and at opening  
681 prospects for synergistic efforts that will allow the food community to face the oncoming  
682 challenges.

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