Data literacy in the new EU DigComp 2.2 framework how DigComp defines competences on artificial intelligence, internet of things and data

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Abstract

Purpose – The purpose of this paper is to analyse data literacy in the new Digital Competence Framework for Citizens (DigComp 2.2). Mid-2022 the Joint Research Centre of the European Commission published a new version of the DigComp (EC, 2022). This new version focusses more on the datafication of society and emerging technologies, such as artificial intelligence. This paper analyses how DigComp 2.2 defines data literacy and how the framework looks at this from a societal lens.

Design/methodology/approach – This study critically examines DigComp 2.2, using the data literacy competence model developed by the Knowledge Centre for Digital and Media Literacy Flanders-Belgium. The examples of knowledge, skills and attitudes focussing on data literacy ($n = 84$) are coded and mapped onto the data literacy competence model, which differentiates between using data and understanding data.

Findings – Data literacy is well-covered in the framework, but there is a stronger emphasis on understanding data rather than using data, for example, collecting data is only coded once. Thematically, DigComp 2.2 primarily focusses on security and privacy (31 codes), with less attention given to the societal impact of data, such as environmental impact or data fairness.

Originality/value – Given the datafication of society, data literacy has become increasingly important. DigComp is widely used across different disciplines and now integrates data literacy as a required

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competence for citizens. It is, thus, relevant to analyse its views on data literacy and emerging technologies, as it will have a strong impact on education in Europe.

Keywords DigComp 2.2, Data literacy, Artificial intelligence, Internet of things, Media literacy, Media education, Competences

Paper type Research paper

Introduction

The past 40 years have been characterised by strong technological innovations – some radical and some incremental – mainly based on the digitalisation of almost all sectors in society. The emergence of the internet, the integration with mobile technology, the evolution towards Web 2.0, the rise of social media and the advent of artificial intelligence or AI are all processes driven by digitalisation and innovation. Fundamentally linked to this process of digitalisation is the process of datafication.

Many authors agree that datafication is a new phase of innovation that offers huge potentials in terms of smart cities, smart environments, personalised services, user friendly recommendation systems, etc. For each process that is digitalised, new data is created both intentionally and non-intentionally (Zuboff 2015, 2019). This data can be captured, stored, analysed and used for different purposes. Advances in algorithms and artificial intelligence make that more and more meaningful insights can be extracted from (big) sets of data.

However, others point to the dangers of algorithm bias, loss of serendipity, privacy concerns, social sorting of customers and citizens, etc. At a much more fundamental level, Zuboff (2015) argues that datafication is not a technological process or an inevitable technical effect. For her, datafication plays a key role in the establishment of a new form of information capitalism that "[. . .] aims to predict and modify human behavior as a means to produce revenue and market control" (Zuboff, 2015, p. 75). Couldry and Mejias make a similar analysis claiming data is about "[. . .] the capture and control of human life itself through appropriating the data that can be extracted from it for profit" (2018, p.xi).

Together with the changes in media and technology came the call for new forms of literacy (Pangrazio and Sefton-Green, 2021). The general feeling is that especially young people need a new set of skills related to data, to be able to function in our current and future data-driven society. As Carmi *et al.* (Carmi *et al.*, 2020) argue:

> (This) lack of data literacy opens citizens up to risks and harms–personal, social, physical and financial–but also limits their ability to be proactive citizens in an increasingly datafied society (p. 2).

Yet, what these precise competences are or should be is currently hotly debated. This is logical as the debate on what data literacy is has not yet been stabilised.

In recent years, several new forms of literacy have been suggested in relation to the datafication of society (Van Audenhove *et al.*, 2020). Different authors see a need for data literacy (Bhargava *et al.*, 2015), algorithm literacy (Oldridge, 2017), coding literacy (Vee, 2017) or data infrastructure literacies (Gray *et al.*, 2018). We prefer the term data literacy because data is the defining aspect in the process of datafication.

This discussion on new forms of literacies is not new. In the 1970s, media literacy emerged as a result of the new medium of television (Masterman, 1985). The focus of media literacy lies on understanding media and media processes (production, language, representation and audience) (Buckingham, 2003). After 20 years, from the 1990s onwards, as the result of computers, internet and digitalisation, the focus shifts to digital literacies. Early conceptualisations of digital literacy often refer to access and operational proficiency (van Dijk, 2020). More recent digital literacy competence models integrate analytical and critical skills. They list a more extensive list of specific skills and competences (Iordache *et al.*, 2017). Competence models over time tend to become more complex, more encompassing and nuanced and more stable. The development of competence models is almost directly linked to a theoretical discussion about technological change and the social consequences of that change.

One of the more recent attempts to integrate data literacy in an overall competence framework is the new version of the EU DigComp Framework. The DigComp Framework is one of the most widely used digital competence frameworks in Europe and beyond (Barboutidis and Stiakakis, 2023; Bartolomé and Garaizar, 2022; Mattar *et al.*, 2022). The new 2.2 version aims to "[. . .] engage citizens confidently and safely with digital technologies, taking account of emerging technologies, such as Artificial Intelligence (AI), the Internet of Things (IoT), (and) datafication" (Thornton, 2022). The competence framework as such has not changed. However, the framework is supported by new examples of knowledge, skills and attitudes. According to the DigComp 2.2:

> These examples illustrate new focus areas with the aim to help citizens engage confidently, critically and safely with everyday digital technologies, but also with new and emerging technologies such as systems driven by artificial intelligence (AI) (Vuorikari *et al.*, 2022, p. 2).

The questions of this article are:

Q1. How does DigComp 2.2 define data literacy?

Q2. What are the underlying assumptions?

Q3. How does it define the competences needed?

These questions are important to focus on, as DigComp is widely used across different disciplines and now integrates *data literacy* as a required competence area for citizens. It is, thus, relevant to analyse its views on *data literacy* and emerging technologies, as it will have a strong impact on education in Europe. To answer the questions, we will subsequently:

- review the current theoretical discussion on data literacy;
- present the high-level data literacy competence model (DLCM) as defined by the Knowledge Centre for Digital and Media Literacy Flanders-Belgium;
- briefly introduce the EU DigComp 2.2 Framework;
- outline the methodology used to analyse DigComp 2.2;
- present our analysis of DigComp 2.2 itself in relation to the DLCM and present a thematic analysis; and
- present the conclusions of our work.

The discussion on data literacy

As indicated, the discussion on data literacy is in full flux. Different disciplines and groups of scholars hold rather different views on how data literacy should be defined and, therefore, what data literacy competences people should have. We identify three main fields of discussion: the open data field, the STEM field and the social science field.

The first field is the open data field, which focusses on providing access to as much data as possible and to make data freely available to society (Baack, 2015; Couldry and Powell, 2014). The movement started from the premise that open data can contribute to a participatory democracy in which citizens use data themselves, aimed at influencing politics and policymaking processes. This, however, assumes a high level of knowledge about data, processing, structuring, analysing and presenting data. Over the years, this community started to realise that not every citizen has the necessary knowledge to deal with data in this way (Carlson and Stowell Bracke, 2015; Frank and Walker, 2016). As Boychuk *et al.* (2016) note:

> Data literacy is presented as imperative for understanding complex datasets, but many open government data initiatives do not address this skill, nor do they clearly lay out plans to teach this skill to the public (p. 4).

Hence, there is a growing interest within this movement for data literacy. Within this type of literature, the emphasis is mainly on being able to use data and less on understanding the role of data in society (Gray *et al.*, 2018; Raffaghelli and Stewart, 2020; Van Audenhove *et al.*, 2020). This approach to data literacy is often utilitarian, as most citizens do not possess the required competences to be able to properly make use of the data, because of a lack of competences focussing on understanding the data. This is something Gray *et al.* (2018) also state in their paper, calling for initiatives that extend beyond data science to encompass data sociology, data politics and broader public engagement with digital data infrastructures.

The second field is the field of STEM education in its broadest form, both at the level of primary, secondary and tertiary education. The emphasis here is on educational innovation through the integration of (big) data, algorithms and AI, into existing curricula and subjects that are aligned with these topics (Bhargava *et al.*, 2015; Csernoch and Biró, 2015; MacMillan, 2015). The overall objective is, on the one hand, to teach students how to use data sets, algorithms and AI in a playful way (secondary and higher education). On the other hand, students are taught to critically reflect on data and the role of data in society. In general, however, much of this literature focusses heavily on being able to use data and less on understanding data. For tertiary education, for example, Carlson and Stowell Bracke (2015) observe that:

> With researchers facing new requirements and expectations for managing, sharing and curating their data, it is critical that they have the knowledge and skills needed to respond effectively. However, competencies in working with data are often not included as a part of a student's formal education. Students that do acquire proficiencies with data generally gain their skills in an ad hoc manner on the job and at the point of need (our emphasis) (p. 96).

Related to this field is also the discussion on *data literate educators and schools* that focusses on using data more generally throughout the curriculum (Mandinach and Jimerson, 2016; Ndukwe and Daniel, 2020; Reeves and Honig, 2015).

The third field is the field of social sciences reflection on data. This field is consistent with the reflection on data, people and society that takes place in the social sciences. Some of this literature looks at *personal data literacy* (Pangrazio and Selwyn, 2019) and the role of personal data and its consequences for the individual user. Other authors discuss the role of data in broader social processes (Zuboff 2015, 2019; Gray *et al.*, 2018). This field is very much in line with the discussion on media literacy and the role of media in society (Van Audenhove *et al.*, 2020). To come to grips with a broader understanding of data literacy, Carmi *et al.* (2020) introduce the concept of *data citizenship* as "[...] a framework that outlines the importance of citizens having a critical and active agency, at a time when society's datafication and algorithmically-driven decision-making has become normalised" (p. 10). The framework consists of three areas:

(1) data thinking – citizens' critical understanding of data (e.g. understanding data collection and data economy);

(2) data doing – citizens' everyday engagements with data (e.g. deleting data and using data in an ethical way); and

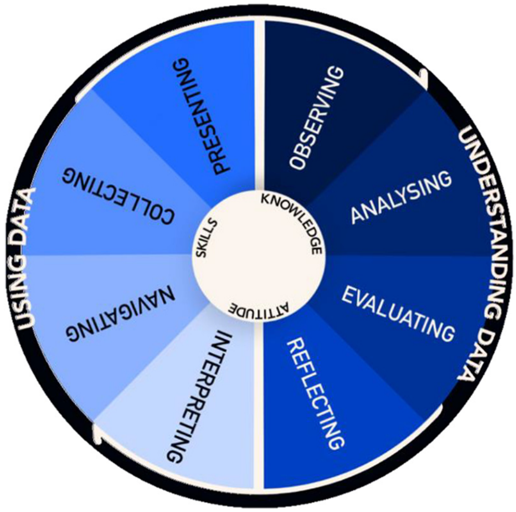
(3) data participation – citizens' proactive engagement with data and their networks of literacy (e.g. taking proactive steps to protect individual and collective privacy and well-being in the data society as well as helping others with their data literacy) (Carmi *et al.*, 2020).

We observe that within social and educational sciences, the prevailing focus in the literature is on the proficiency in using data, especially in relation to statistics, mathematics, data science and big or open data. We see a similar conclusion in the systematic review of Godaert *et al.* (2022), who note that digital competence assessments of children focus much less on the DigComp 2.1 areas of "problem solving" and "safety". They also see emphasis on skills and use, less on knowledge and attitudes. Gebre (2022), who reviewed the literature on K-12 data literacy education and how the included articles define data literacy, finds that data literacy education research focusses on data skill development in relation to data use and looks less at data literacy from a perspective of "human agency" and how to live in a datafied society.

Data is always strongly influenced by context, and it is collected, handled and interpreted by people with their own values, norms and prejudices, which can perpetuate inequality and exclusion. So even in "using" data, citizens need to be able to critically "understand" and look at the broader narrative of data in society and the contexts to which the data belongs, from collecting to interpreting to presenting the data. "Although reasoning with data is rooted in epistemic processes, the stances people take are—and should be—influenced by values [and] concerns" (Polman *et al.*, 2022, p. 1). As Lee *et al.* (2022) state, data literacy or data science education, need to put more emphasis on data justice, inclusion and plurality. Data literacy is moving toward this more critical focus, however, as was found in other articles, educational activities primarily focus on data use without necessarily critically reflecting on societal repercussions, bias in data, data fairness [. . .] (Godaert *et al.*, 2022; Gebre, 2022). The DLCM, which will be discussed below, seeks to tackle these issues by offering a comprehensive outline of essential competences required for a well-rounded data literate citizen and enabling educators to map their initiatives on a user-friendly model.

The data literacy competence model

In this article, we start from the DLCM, developed by the Knowledge Centre for Digital and Media Literacy Flanders-Belgium (Figure 1) (Seymoens *et al.*, 2020). This model is largely based on the model of media literacy by the same centre. Based on existing literature, a model was presented and validated by a group of social science scholars with a background in media and data literacy. The aim of the model is to provide a high-level common understanding of data literacy in Flanders-Belgium. The model can be applied to evaluate specific data literacy initiatives in terms of competences they address (Seymoens *et al.*, 2020). It can also be used by educators to develop and map specific data literacy initiatives that focus on the different competences. In Flanders-Belgium, the model is used to map and develop data literacy initiatives developed by the Knowledge Centre. It is also used to introduce and explain the concept of data literacy to policymakers.



Source: Figure by authors

Figure 1.
Data literacy competence model (mediawiijs.be)

The model comprises two major competence clusters *using data* and *understanding data* (Mediawijs, 2020b). Competences refer to the knowledge, skills and attitudes that allow individuals to act adequately in a given situation (Mediawijs, 2020a). For each of those two clusters, four broad competences are identified for data literacy. The competence clusters are defined in more detail as:

Using data or the knowledge, skills and attitudes to use data actively and creatively:

(1) *interpreting*: being able to read a graph, table or list of data and understand what they mean;

(2) *navigating*: finding your way through a collection of different types of data and ways they were processed and being able to extract the message or what you need;

(3) *collecting*: being able to set up a process to collect raw data and organise an analysis; and

(4) *presenting*: being able to present and visualise the results of a data analysis in a targeted manner, tailored to an audience.

Understanding data or the knowledge, skills and attitudes to critically and consciously assess the role of data:

(1) *observing*: being able to observe how data is communicated and used;

(2) *analysing*: being able to analyse the individual and social consequences of the way how data is communicated and used;

(3) *evaluating*: being able to evaluate whether those consequences are harmful or constructive; and

(4) *reflecting*: being able to reflect on how you and others communicate and use data, being able to adjust to minimise harmful consequences.

The cluster of competences for using data is more practice-oriented. This is in line with the focus of the open data movement field and partly also the education field on being able to actually *use data*. These fields see data literacy often as functional or goal-oriented. Starting with a problem that can be or needs to be solved by using data. In its definition of data literacy, the *Education Development Centre* lists data literacy competences as: "(He/she/they) can identify, collect, evaluate, analyse, interpret, present and protect data" (EDC, 2016). The order in which the competences are listed reveals the goal-oriented way of thinking. *Collecting* comes before *interpreting*. Yet, being able to collect data requires a lot more knowledge and experience than just interpreting data.

The model of the Knowledge Centre (2020), therefore, follows the levels of literacy in relation to data. It starts with the questions: Can I read data? Can I navigate different types of data? Can I organise data to analytically understand them? Can I collect existing and new data? Can I present and communicate those data? The cluster of competences for understanding data is more oriented towards critically and consciously understanding the role of data in society, personal life, etc. This focus is often neglected or underdeveloped, especially by those authors who have a background in statistics, data analytics or computer sciences. These competences are closely linked to reflections on the role of data in social science. The DLCM (2020) highlights the importance of bringing both competence clusters into one overarching model, as citizens need to possess competences in both using and understanding data to effectively participate and navigate our data-driven society. However, we see a much broader focus within society on being able to use data and its relation to numeracy and statistics, than on understanding data and critically looking at these data (Gebre, 2022; Godaert *et al.*, 2022).

The EU DigComp 2.2 framework

On March 22, 2022, the Joint Research Centre of the European Commission published a new version of the Digital Competence Framework (EC, 2022) (Figure 2). The DigComp Framework is probably one of the most widely used digital competence frameworks. The tool can be used by member states and organisations within member states to develop

Source: Figure published by the European Union, 2022

Figure 2. DigComp 2.2: digital competence framework for citizens (Vuorikari *et al.*, 2022)

digital competency policies and/or to assess the digital competences of its citizens, as mentioned in the document. It strives to create a common baseline for digital competences. The current model is based on 21 digital competences, which are divided in separate categories, or components. Within this framework, the model identifies five main components, namely, information and data literacy, communication and collaboration, digital content creation, safety and problem-solving (Figure 2).

The first European digital competence framework was published in 2013 by the Joint Research Centre in collaboration with relevant stakeholders, such as policymakers, educators and researchers. The framework has been updated and extended several times to come to grips with the ever-changing digital society (Carretero Gomez *et al.*, 2017; Vuorikari *et al.*, 2016). In 2021, the European Commission established several working groups to update the framework yet again. The new version 2.2 aims to "[. . .] engage citizens confidently and safely with digital technologies, taking account of emerging technologies, such as Artificial Intelligence (AI), the Internet of Things (IoT), (and) datafication" (EC, 2022). The competence framework as such has not changed. However, the framework is supported by new examples of knowledge, skills and attitudes in the three identified domains. According to the DigComp 2.2:

> These examples illustrate new focus areas with the aim to help citizens engage confidently, critically and safely with everyday digital technologies, but also with new and emerging technologies such as systems driven by artificial intelligence (AI) (Vuorikari *et al.*, 2022, p. 2).

Europe has widely recognised and embraced DigComp as the main model for digital competences. In Flanders, for example, Digisprong, the government's knowledge centre on digitalisation in education, used Digcomp 2.1. to develop their teacher guides, an opensource learning platform explaining teachers how to self-assess their digital competences. For students, the framework was used to help ground the educational target goals around "digital competences". DigComp is also used within the educational context of other countries. In The Netherlands, it serves as the basis of a competence measurement tool for educational innovation, mapping how digital literacy is covered in higher education curricula (Versnellingsplan Onderwijs met ICT, 2022), and in France, the ministry of education developed a reference framework for digital skills from primary school to university, inspired by DigComp (éduscol, 2023). DigComp is also used by researchers to support and develop their digital competence assessments of citizens or to analyse educational practices. Because DigComp is widely used as an assessment tool in research and in education throughout Europe, it is important to analyse the framework to understand its potential and limitations.

Research set up, methodology and coding

What is new in the DigComp 2.2 Framework are the examples that reflect new emerging technologies and datafication in the domain of AI and IoT. In our contribution, we aim to critically analyse the DigComp 2.2 Framework. We do this by focusing on an analysis of the examples, as they are meant to: "[. . .] motivate education and training providers to update their curriculum and course material to face today's challenges" (Vuorikari *et al.*, 2022, p. 2).

The DigComp 2.2 Framework lists 259 concrete examples. As a first step of our approach, we carefully read all examples and selected all those that have a bearing on data, algorithms, IoT and AI. As mentioned, AI and IoT are the two new domains the DigComp framework explicitly mentions, so we included these together with data and algorithms, as algorithms are linked to decision-making (which is one of the thematic codes). Algorithms can also include AI, making it relevant to focus on. In principle, if the word *data* appears in an example, even as an explanation or sub-example between brackets, then we have included the example. We have left out examples that refer to digital skills and technology more generally. This led to a sample of 84 examples for our further analysis.

Next, the 84 examples on data were coded according to the following process:

- The first author of this article coded the 84 examples according to the eight competences identified in the DLCM: *interpreting, navigating, collecting, presenting* and *observing, analysing, evaluating* and *reflecting*. Each example was given only one code for one of the eight competences. If an example referred to two possible competences, then a decision was taken to code the most prominent one. The first author introduced a separate competence of *processing* between *collecting* and *presenting*, as this seemed to be missing (see later).
- The author also coded the 84 examples thematically based on the content of the example. For the latter, a coding scheme was progressively developed while coding. In line with the logic of DigComp 2.2, a broad distinction was introduced between *data* and *artificial intelligence* with more specific sub-themes identified and added while coding.
- Two of the co-authors independently coded all 84 examples according to the DLCM (with the extra competence of *processing)* and using the thematic coding scheme developed by the first author. A field for comments was added to note any potential questions or issues during the coding. This led to three separate fully coded files.
- In a joint session, the three coding authors then compared their coding, discussed the choices made, discussed divergences in the coding, agreed on interpretations of coding, clustered the thematic coding into a more comprehensive system and finalised the coding into a joint table for analysis (Appendix). We chose this approach to allow for an active discussion and final agreement on the coding between the three coders.

In what follows we describe the discussion by the coding authors, the reflections made and the decisions taken in relation to coding. For most entries (around 80% of the cases), there was convergence on coding both in terms of the DLCM and thematic coding. Entries starting with words like *Aware* or *Knows* clearly refer to competences in the cluster *understanding data*. Other entries starting with words such as *Knows how, Can, Avoids* and *Are able to,* most often refer to *using data*. For some entries, however, there was divergence on the interpretation between *using data* or *understanding data* and its sub-competences, leading to different codes by the three coders. The authors then decided to categorise entries that *presume* an active behaviour by the user under the cluster *using data,* even when elements of *understanding data* were also present. Again, only one code was attributed per example.

In the cluster *using data*, a discussion unfolded around the competence of *collecting data.* In the DLCM, *collecting data* is described as: *being able to set up a process to collect raw data and organise an analysis*. Yet, in DigComp 2.2, only one example explicitly refers to *collecting data* in the strict sense of the word. Example 36 states: *Knows how to collect digital data using basic tools such as online forms and present them in an accessible way (*e.g. *using headers in tables).* In our view, nine examples in the cluster *collecting data* would better fit under a new heading of *processing data.* Different examples in the DigComp 2.2 Framework, such as *Competence 4.2: Protecting Personal Data and Privacy* would fit in such a new category. Example 175 states: *Able to encrypt sensitive data stored on a personal device or in a cloud storage service.* This is clearly a competence that requires the user to act but has less to do with collecting data as such. The DigComp 2.2 *Competence 2.6: Managing Digital*

Identity raises the same issue. Example 111 states: *Able to verify and modify what type of metadata (*e.g. *location, time) is included in pictures being shared to protect privacy.* In general, the competences related to identity and privacy are not easy to code in the competences of the DLCM. We, therefore, suggest introducing a new category *processing data* which could encompass not only processing of raw data but also *protecting* personal data.

In the cluster *understanding data,* coding seemed to be more straightforward. Discussion sometimes arose between *evaluating* and *reflecting. Evaluation* in the DLCM refers to being able to evaluate whether consequences are harmful or constructive. Example 42 related to managing data states: *Watchful of accuracy when evaluating sophisticated representations of data (*e.g. *tables or visualisations as they could be used to mislead one's judgement by trying to give a false sense of objectivity). Reflecting* in the DLCM refers to the capacity of the individual to ethically assess the social implications of data. Example 165 related to programming is a good illustration: *Considers ethics (including but not limited to human agency and oversight, transparency, non-discrimination, accessibility and biases and fairness) as one of the core pillars when developing or deploying AI systems (AI).* But the line between the two is not always that clear and often needs interpretation. Example 54 in relation to the interaction through technology states: *Open to AI systems supporting humans to make informed decisions in accordance with their goals (*e.g. *users actively deciding whether to act upon a recommendation or not) (AI).* We considered that this goes beyond just *evaluating* the consequences of using technology and coded this under *reflecting.*

For the thematic coding, we first introduced the distinction between *data* and *AI.* This is a distinction made within the DigComp 2.2 Framework itself. All examples related to artificial intelligence are followed by a symbol *(AI)* in the document. At first, we coded examples with very specific thematic codes. However, often this resulted in one or two codes per theme. We, therefore, decided to cluster examples in larger themes. *Identity, Privacy and Ethics* for instance is a larger theme that well describes the importance DigComp 2.2 allocates to this theme in the framework. We kept some of the smaller themes such as *Citizenship* and *Environmental Impact* because it is important to indicate that DigComp 2.2 does reflect on data and AI in a broader societal context. As already mentioned, only example 36 refers to actually *collecting data* which would get much more attention in a STEM, educational or scientific approach to data literacy. Example 36 states: *Knows how to collect digital data using basic tools such as online forms and present them in an accessible way (*e.g. *using headers in tables).*

Critical analysis of the DigComp 2.2 framework

From the 84 examples referring to data literacy in the DigComp 2.2. Framework, 31 can be coded under *using data* and 53 under *understanding data.* A first observation to make is that DigComp 2.2 clearly emphasises *understanding data* more than being able to *use* or *handle data*. In this respect, DigComp 2.2 approaches data literacy from the more sociological field and less from an open data field or STEM field, as will be confirmed by our further analysis. In the first subsection, we will analyse DigComp 2.2 against the DLCM. In a second section, we will provide a thematic analysis of the examples related to data and AI. From the 84 examples, 49 refer to data and 35 specifically to AI. The focus on AI does not come as a surprise as DigComp 2.2 explicitly states that version 2.2 would include a focus on AI.

Analysing DigComp 2.2 against the data literacy competence model

In the coding of the cluster *using data* (Table 1), coding is uneven over the different categories *interpreting, navigating, collecting, processing and presenting. Interpreting (3),* *navigating (7)* and *collecting data (1),* which refer to an active and goal-oriented use of data, only encompasses a limited number of examples. Within *navigating data,* examples 35 and 75 explicitly refer to an open data interpretation of data literacy. Example 35 states: *Knows that open data repositories exist where anyone can get data to support some problem-solving activities (*e.g. *citizens can use open data to generate thematic maps or other digital content).* Example 75 notes: *Knows how to monitor public spending of local and national government (*e.g. *through open data on the government's website and open data portals).* The rest of the examples are more hands-on navigating or searching information and data.

Processing and *presenting data* are mentioned 9 and 11 times, respectively. At first sight, one would presume that DigComp 2.2, thus, puts a lot more emphasis on using existing data and data sets than on creating or collecting own data. However, even within these categories, not that much emphasis goes to actively handling data. Example 40 is such an example in processing data: *Can use data tools (*e.g. *databases, data mining and analysis software) designed to manage and organise complex information, to support decision-making and solving problems.* However, within the category of *processing data*, seven examples have a privacy and security focus. These include the handling of sensitive data on personal devices (example 175) or verification of metadata (example 111).

In the category of *presenting data*, several examples focus on processing data to present data to an audience. This ranges from applying basic statistics to visualise data (example 37), to interacting with and manipulating data visualisations. Example 38 says: *Knows how to interact with dynamic data visualisation and can manipulate dynamic graphs of interest (*e.g. *as provided by Eurostat and government websites).* In this category, multiple examples refer to the more creative and goal-oriented handling of data, such as supporting your own ideas and opinions by creating digital content (example 124) or combining various types of digital data (example 127).

In relation to creative use, example 131 focuses on the creation of infographics and posters with software and example 133 focuses on the integration of digital technologies, hardware and sensor data to create new artefacts. Some of the examples used require highly complex skills and almost move into professional use of data. Example 134 focusses on: *Knows how to incorporate AI edited/manipulated digital content in one's own work (*e.g. *incorporate AI generated melodies in one's own musical composition). This use of AI can be controversial as it raises questions about the* role *of AI in artworks and, for example, who should be credited.* Or 246: *Open to engage in collaborative processes to co-design and co-create new products and services based on AI systems to support and enhance citizens' participation in society (AI).* It becomes clear from this analysis and the concrete examples that a lot of emphasis is placed on presenting data in a creative and clear way. The processing of data is focused not only on the analysis of the actual data, but also on processes related to dealing with privacy sensitive information and being able to check metadata for example. Only one example is focusing on data collection.

Coding on data literacy competence model				
Using data Interpreting	Navigating	Collecting	Processing	Presenting
3 31	7	1	9	11

Source: Table by authors

Table 1.
DigComp 2.2 Coding on data literacy competence model: using data

As indicated, 53 examples are coded in the cluster of *understanding data* (Table 2). Coding is more equally distributed over the categories *observing (18), analysing (9), evaluating (16) and reflecting (10).* The category *observing* predominantly comprises rather simple things users need to know about data and how data is created in a digital society, such as knowing that communication services are free because they are partly paid for by user data (example 43) or that data needs to first be digitally encoded before it can be processed and analysed (example 32). Example 43 states: *Knows that many communication services (*e.g. *instant messaging) and social media are free of charge because they are partly paid for by advertising and monetising user data. Observing* also explicitly refers to knowledge about EU-policy in relation to data, especially with a focus on privacy and security, for example, knowledge about the rights of access, rectification and erasure or right to be forgotten.

In the category *analysing*, we find examples that require a deeper understanding of the underlying processes of data, with examples emphasising the different aspects of the role of AI in personalisation (example 4) and large amounts of data collection with sensors and applications such as wearables and virtual assistants (example 32). The examples we coded in this category seem to refer to the working of AI and increasing integration of AI into various aspects of digital technology and its implications for users.

In the DLCM, the category *evaluating* looks at whether consequences are harmful or constructive. This weighing of consequences is present in 16 examples. Example 14 notes the ability to weigh the benefits and disadvantages of using AI-driven search engines, and example 117 notes that users should be able to identify positive and negative implications of data use, especially when it comes to personal data use for AI-driven technology. A lot of the examples in this category refer to competences necessary to assess bias, accuracy, unrecognised processes of AI-systems, which are indeed important competences in relation to AI.

R*eflecting* in the DLCM refers to the minimising of harmful consequences and the societal impact, referring to the ethical considerations (example 79) and lifelong learning in the context of AI (example 225), highlighting the importance of ethical awareness and continuous learning related to all things AI, although the latter is a competence only few people will actually achieve. Example 79 probably reflects this the best: *Readiness to contemplate ethical questions related to AI systems (*e.g. *in which contexts, such as sentencing criminals, should AI recommendations not be used without human intervention) (AI)?* From this analysis it becomes clear that most examples in the observing category relate to insights in the way data is being used (e.g. as a currency for free services) and the rights people have related to their data, for example the right to be forgotten. The second biggest category of examples focus on evaluating, which also takes a more normative approach (e.g. evaluating whether something can be harmful).

Analysing DigComp 2.2 thematically

In the thematic analysis, we made an overall distinction between *data* and *AI* (Tables 3 and 4). In all, 49 examples refer to *data* and 35 to *artificial intelligence*. For the examples

Table 2. DigComp 2.2 Coding on data literacy competence model: understanding data

Coding on data literacy competence model Understanding data			
Observing	Analysing	Evaluating	Reflecting
18	9	16	10
53			

Source: Table by authors

coded under the thematic category of *data,* three are very general in terms of *understanding data*. Examples 154 and example 162 highlight the ability to recognise and work with input and output data in simple programs. A second thematic category is the one on *problem-solving*. Only four examples fit this category and zoom in on understanding how data is utilised in various domains, especially in problem-solving and decision-making processes. Example 40 states: *Can use data tools [...] designed to manage and organise complex information, to support decision-making and solving problems*. Example 40 is a direct illustration of the *open data field* approach to media literacy.

The rest of the examples in the overall category *data* are coded in the categories *security (7), identity, privacy and ethics (12), representation of data (14) transparency (5), environmental impact (2)* and *citizenship (2)*. An example representative for *security* is example 167: *Knows about measures to protect devices (*e.g. *password, fingerprints and encryption) and prevent others (*e.g. *a thief, commercial organisation and government agency) from having access to all data.*

Here, we highlight interesting insights from four categories, namely, representation of data, transparency, environmental impact and citizenship. The examples coded in *representation of data* have to do with being able to create and present data and being able to read data in its different forms. Example 124: *Knows how to create digital content to support one's own ideas and opinions (*e.g. *to produce data representations such as interactive visualisations using basic data sets such as open government data)*. Example 124 can also be seen as an example of the *open data field* approach to data literacy. In fact, in the category of *representation of data*, more entries could be interpreted in this way. The category of *transparency* is closely related to the former, revolving

Thematic coding
Data

Understanding data	Problem-solving	Security	Identity, privacy and ethics	Representation of data	Transparency	Environmental impact	Citizenship
3	4	7	12	14	5	2	2
		Security and privacy	Representation	Societal impact			
3	4	19	19	4			
				49			

Source: Table by authors

Table 3.
Thematic coding: data

Thematic coding
Artificial intelligence

Understanding AI	Identity, privacy and ethics	Recommender systems	Search	Bias in algorithms	Environmental impact	Citizenship
5	12	2	2	8	3	3
	Security and privacy	Bias	Societal impact			
5	12	12	6			
		35				

Source: Table by authors

Table 4.
Thematic coding: artificial intelligence

around the importance of verifying information (sources) from the internet and recognising possible biases in data, particularly on platforms like social media (example 18). Recognising that data can be shared in a biased way and data handlers can have a biased point of view, strongly relates to the concepts of data feminism and data justice, requiring a critical interpretation of data.

The category on *environmental impact* only has two examples that stress the positive and negative impacts of technology. These examples focus on the intersection of digital technology and the environment, emphasising the potential for digital technologies to contribute to energy efficiency (example 208) and underscoring the importance of understanding and mitigating the environmental impact of digital practices, for example, carbon emissions (example 203). The category on *citizenship* has examples that again are in line with the *open data field* view, such as, example 75: *Knows how to monitor public spending of local and national government (*e.g. *through open data on the government's website and open data portals).*

For the 35 examples coded on the overall theme of artificial intelligence, 5 are very general in nature, for example, awareness about the uncertain impact of AI. Example 251 notes: "Aware that AI is a constantly-evolving field, whose development and impact is still very unclear (*AI*)." Again, the theme of *identity, privacy and ethics* has a lot of examples, 12 in total. The examples are very much in line with the examples related to *data*. In relation to the theme of *AI*, examples state AI awareness and transparency, highlighting different aspects of understanding and being aware of artificial intelligence (AI) systems, for example, user profiling or black box decision-making (examples 5 and 105). The next three themes *recommender systems, search* and *bias in algorithms* refer to the working of AI and warns us for possible biases related to AI and underlying algorithms, which relates to the abovementioned category *transparency*. The examples in these themes underscore the importance of being critical, informed and discerning when using AI-driven tools and platforms, like search engines (example 14). This especially when it comes to AI bias, for example, AI algorithms embodying a political message, thus having certain negative consequences like perpetuating stereotypes (example 21).

The last two themes are in line with the societal impact we already saw under *data*, that refer to *environmental impact* and *citizenship.* The examples given are highly similar. In relation to *environmental impact*, example 209 warns that we should be: *Aware that certain activities [. . .] are resource intensive processes in terms of data and computing power. Therefore, energy consumption can be high which can also have a high environmental impact (AI).*

Discussion

We observe that within social and educational sciences, the prevailing focus in the literature is on proficiency in *using data*. When articles focus on *using data*, the primary areas of focus are typically statistics, numerical proficiency and data handling. However, there is a growing trend towards enhancing the critical understanding of data. When the focus is on *understanding data*, we see links with equity and inclusion, ethics and citizenship. This is in line with the DigComp framework. Furthermore, there is an emphasis on the interconnectedness with media literacy, mis- and disinformation and data journalism. There is much less attention on personal data protection and privacy in the literature, aspects of notable prominence in the DigComp.

Other DLCMs and frameworks, however, often focus on *data usage skills*. A well-known model is that of Risdale *et al.* (2015) that identifies 22 competences for three proficiency levels. The model is an interesting start for data literacy, but is unbalanced because it mainly focusses on *using data* and, thus, looks less at participation, empowerment or citizenship. Existing models tend to follow the steps and logic we see in research and, consequently, start with searching for and *collecting data*. In other words, they often assume a research question aimed at actively searching/collecting appropriate data and using data to improve services. An example of this is the framework developed by Gummer and Madinach (2015). This model provides a useful overview for teachers on what competences they need to effectively use data to improve education, while also taking into account data ethics in later publications (Mandinach and Jimerson, 2022). This trend toward a more critical data literacy is also noticeable in recent literature, such as the data citizenship framework put forward by Carmi *et al.* (2020).

In contrast to older models, the DLCM starts with being able to *interpret data*. From a didactic point of view and in terms of necessary knowledge acquisition, this is more logical in structure (Seymoens *et al.*, 2020) and considers not just researchers, librarians or students, but all citizens. As mentioned above, policymakers and educators in Europe and worldwide direct their attention towards specific topics and competences put forward by the DigComp framework, thereby influencing the capabilities of children, young people, but also other citizens. This affects how young people are and will be able to actively engage as future voters, members of the workforce and parents and partners. And it not only bears significance in the context of participation and engagement, but also has implications for emerging jobs, such as bias auditors, and the growing demand for professions like data scientists and engineers. It will also have an impact on and reshape existing occupations. For instance, teachers will need proficiency in working with educational data to enhance their teaching, or health professions will need to adapt to use AI- and e-health tools more effectively and safely.

The importance of this critical data literacy education is closely tied to the discussions surrounding data justice. As Dencik and Sanchez-Monedero (2022) state, this concept highlights the importance of considering data as an integral part of social justice, rather than something technical and purely numerical. In an increasingly data-driven society where data has become a valuable commodity (Zuboff, 2015), the perspectives of data justice, data feminism and critical data literacy education, which emphasise u*nderstanding* data and datafication, gain even more relevance. While DigComp does not extensively address these aspects, there is a noticeable shift within the framework towards a more comprehensive and critical understanding of data literacy, albeit primarily at the level of individual data protection and privacy.

Conclusion

Reflections on the data literacy competence model

The goal of the DLCM is to provide a high-level model to orient a common understanding of data literacy competences within Flanders-Belgium. In this article, we used it to analyse the examples of the DigComp 2.2 Framework. This worked rather well as the DLCM clearly highlights the difference between on the one hand *using data* and *understanding data* and on the other hand differences in attention within the *using data category* with a clear focus on *presenting* data. As noted, while coding, we missed the specific category of *processing* data which covered many examples in the DigComp 2.2 Framework.

It forces us to reconsider and reconceptualise our own model. The model places significant emphasis on fostering critical thinking, but it is imperative that we conduct a more in-depth assessment of the *understanding data* component. We intend to thoroughly examine the model to ensure it accommodates competences related to data justice and data fairness. We will also need to test and validate the adapted model by mapping educational practices focussed on both *using* and *understanding data*.

Today’s society requires citizens to possess competences for *using data* and *understanding data*. However, it is important to note that using data does not inherently foster a critical understanding (Van Audenhove *et al.*, 2020; Carlson and Stowell Bracke, 2015). Citizens need to be aware of and understand how data works and the potential risks that it can introduce (Polman *et al.*, 2022). *Understanding data* then supports decision-making, participation and adaptability in an ever-changing society.

Reflections on DigComp 2.2

Reading the examples of DigComp 2.2 provides one with the impression that *data literacy* is well covered in the framework. All aspects of data literacy and the different fields of data literacy are covered. Our coding and analysis against the DLCM, however, clearly tells another story. DigComp 2.2 is not neutral, as codes are not distributed evenly among the different DCLM competences. DigComp 2.2 emphasises different themes, and it is clearly inspired by one of the data literacy fields.

A first observation to make is that DigComp 2.2 emphasises *understanding data* much more than being able to *use data*. In this respect, the DigComp 2.2 interpretation of data literacy is more inspired by the sociological field and less from an open data field or STEM field, which build more on *using data*. The more active and strategic use of data involving collecting data or actively using existing data, does not receive much attention. These competences are present but are only referred to in a limited number of examples. As indicated, only one example is coded within the specific category of *collecting data*. This is the reason why we split up *collecting data* in *collecting* and *processing data*. DigComp 2.2 has a lot of examples that can be coded under *processing data*.

Thematically, DigComp 2.2 puts a lot of emphasis on *security and privacy*, a theme less present in literature on data literacy education. Combining Tables 3 and 4, 31 of the 84 examples fit this category. It is logical that a competence framework strives to protect the user. However, in terms of balance, we could ask whether more than one-third of examples should focus on a protectionist approach to data literacy. Especially as other thematic coding such as *representation* and *bias* also have a certain focus on protecting the user. Topics such as *environmental impact* and *citizenship* which figure high in some of the discussions on data literacy are present in the examples, but only with a few observations. Competences related to these themes are essential, as citizens will be able to recognise the limitations of data.

This imbalance will affect the models' users and affect their level of active participation in society. It will also have societal implications. European member states, their policymakers and teachers use the framework to set learning targets and adapt media education curricula. Therefore, citizens' proficiency will be more in line with the competences and topics that DigComp puts forth, possibly resulting in a competence gap. It can also lead to an unbalanced curriculum and can further reinforce inequalities. With the deployment of AI and the continuous use of data, competences in recognising, reflecting on and responding to data- and AI-related injustices are required. When emphasising online privacy over, for example, citizenship-related competences, citizens will become proficient in safeguarding their personal data; however, they may lack the competences to consider ethical and equitable implications.

Seeing the importance of DigComp and its newest 2.2 version, we applaud the strong emphasis of the new framework on data and AI. By doing so, DigComp 2.2 has integrated a strong data literacy focus that will certainly have an impact on education in Europe. However, its lack of focus on actively *using data* might leave many teachers disappointed from a STEM perspective. We note that the framework accentuates "understanding data". If we want to have a more balanced competence framework on data literacy, that includes a stronger focus on data research, statistics and mathematics for being able to *use data*, then that DigComp 2.2. will have to be complemented by another competence model.

The ongoing evaluation and validation of competence models and frameworks are essential to ensure that they are relevant to citizens. This is especially the case for competences related to the digitalisation and datafication of society, which evolves and brings new challenges with the continuous introduction of new software and technologies.

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Appendix

Appendix 1A: DigComp 2.2 Examples per Competence Cluster	
Competence Cluster	**Example**
1. Information and Data Literacy	
1.1 Browsing, Searching and Filtering Data, Information and Digital Content	
2	Aware that online content that is available to users at no monetary cost is often paid for by advertising or by selling the user's data.
4	**Aware that search engines, social media and content platforms often use AI algorithms to generate responses that are adapted to the individual user (e.g. users continue to see similar results or content). This is often referred to as "personalisation". (AI)**
5	Aware that AI algorithms work in ways that are usually not visible or easily understood by users. This is often referred to as "black box" decision-making as it may be impossible to trace back how and why an algorithm makes specific suggestions or predictions. (AI)
8	**Knows how to formulate search queries to achieve the desired output when interacting with conversational agents or smart speakers (e.g. Siri, Alexa, Cortana, Google Assistant), e.g. recognising that, for the system to be able to respond as required, the query must be unambiguous and spoken clearly so that the system can respond. (AI)**
9	Can make use of information presented as hyperlinks, in non-textual form (e.g. flowcharts, knowledge maps) and in dynamic representations (e.g. data).
12	**Intentionally avoids distractions and aims to avoid information overload when accessing and navigating information, data and content.**
14	**Weighs the benefits and disadvantages of using AI-driven search engines (e.g. while they might help users find the desired information, they may compromise privacy and personal data, or subject the user to commercial interests). (AI)**
1.2 Evaluating Data, Information and Digital Content	
18	**Knows the importance of identifying who is behind information found on the internet (e.g. on social media) and verifying it by checking multiple sources, to help recognise and understand point of view or bias behind particular information and data sources**
19	**Aware of potential information biases caused by various factors (e.g. data, algorithms, editorial choices, censorship, one's own personal limitations).**
20	**Knows that the term "deep-fakes" refers to AI-generated images, videos or audio recordings of events or persons that did not really happen (e.g. speeches by politicians, celebrity faces on pornographic imagery). They may be impossible to distinguish from the real thing. (AI)**
21	**Aware that AI algorithms might not be configured to provide only the information that the user wants; they might also embody a commercial or political message (e.g. to encourage users to stay on the site, to watch or buy something particular, to share specific opinions). This can also have negative consequences (e.g. reproducing stereotypes, sharing misinformation). (AI)**
22	Aware that the data, on which AI depends, may include biases. If so, these biases can become automated and worsened by the use of AI. For example, search results about occupation may include stereotypes about male or female jobs (e.g. male bus drivers, female sales persons). (AI)
27	Able to recognise that some AI algorithms may reinforce existing views in digital environments by creating "echo chambers" or "filter bubbles" (e.g. if a social media stream favours a particular political ideology, additional recommendations can reinforce that ideology without exposing it to opposing arguments). (AI)
1.3 Managing Data, Information and Digital Content	
31	**Aware that many applications on the internet and mobile phones collect and process data (personal data, behavioural data and contextual data) that the user can access or retrieve, for example, to monitor their activities online (e.g. clicks in social media, searches on Google) and offline (e.g. daily steps, bus rides on public transport).**
32	Aware that for data (e.g. numbers, text, images, sounds) to be processed by a program, they have to be first properly digitised (i.e. digitally encoded).

(*continued*)

33	**Knows that data collected and processed, for example by online systems, can be used to recognise patterns (e.g. repetitions) in new data (i.e. other images, sounds, mouse clicks, online behaviours) to further optimise and personalise online services (e.g. advertisements).**
34	**Aware that sensors used in many digital technologies and applications (e.g. facial tracking cameras, virtual assistants, wearable technologies, mobile phones, smart devices) generate large amounts of data, including personal data, that can be used to train an AI system. (AI)**
35	**Knows that open data repositories exist where anyone can get data to support some problem solving activities (e.g. citizens can use open data to generate thematic maps or other digital content).**
36	**Knows how to collect digital data using basic tools such as online forms, and present them in an accessible way (e.g. using headers in tables).**
37	Can apply basic statistical procedures to data in a structured environment (e.g. spreadsheet) to produce graphs and other visualisations (e.g. histograms, bar charts, pie charts).
38	**Knows how to interact with dynamic data visualisation and can manipulate dynamic graphs of interest (e.g. as provided by Eurostat, government websites).**
39	**Can differentiate between different types of storage locations (local devices, local network, cloud) that are the most appropriate to use (e.g. data on the cloud is available anytime and from anywhere, but has implications for access time).**
40	**Can use data tools (e.g. databases, data mining, analysis software) designed to manage and organise complex information, to support decision-making and solving problems.**
41	Considers transparency when manipulating and presenting data to ensure reliability, and spots data that are expressed with underlying motives (e.g. unethical, profit, manipulation) or in misleading ways
42	Watchful of accuracy when evaluating sophisticated representations of data (e.g. tables or visualisations as they could be used to mislead one's judgement by trying to give a false sense of objectivity.
2. Communication and Collaboration	
2.1 Interacting through Digital Technologies	
43	**Knows that many communication services (e.g. instant messaging) and social media are free of charge because they are partly paid for by advertising and monetising user data.**
50	**Knows how to identify signs that indicate whether one is communicating with a human or an AI-based conversational agent (e.g. when using text- or voice-based chatbots). (AI)**
51	**Able to interact and give feedback to the AI system (e.g. by giving user ratings, likes, tags to online content) to influence what it next recommends (e.g. to get more recommendations on similar movies that the user previously liked). (AI)**
54	**Open to AI systems supporting humans to make informed decisions in accordance with their goals (e.g. users actively deciding whether to act upon a recommendation or not). (AI)**
2.2 Sharing through Digital Technologies	
56	**Aware that everything that one shares publicly online (e.g. images, videos, sounds) can be used to train AI systems. For example, commercial software companies who develop AI facial recognition systems can use personal images shared online (e.g. family photographs) to train and improve the software's capability to automatically recognise those persons in other images, which might not be desirable (e.g. might be a breach of privacy). (AI)**
59	**Knows how to share and show information from one's own device (e.g. show graphs from a laptop) to support a message being conveyed during a real time online session (e.g. video conference). (RW)**
2.3 Engaging Citizenship through Digital Technologies	
67	**Knows about different types of digital services on the internet: public ones (e.g. services to consult tax information or m ake an appointment in the health care centre), community-based services (e.g. knowledge repositories such as Wikipedia, map services such as Open Street Map, environmental monitoring**

(continued)

	services such as Sensor Community) and private services (e.g. e-commerce, online banking).
69	Knows that all EU citizens have the right to not be subject to fully automated decision-making (e.g. if an automatic sy stem refuses a credit application, the customer has the right to ask for the decision to be reviewed by a person). (AI)
70	Recognises that while the application of AI systems in many domains is usually uncontroversial (e.g. AI that helps avert climate change), AI that directly interacts with humans and takes decisions about their life can often be controversial (e.g. CV-sorting software for recruitment procedures, scoring of exams that may determine access to education). (AI)
71	Knows that AI per se is neither good nor bad. What determines whether the outcomes of an AI system are positive or negative for society are how the AI system is designed and used, by whom and for what purposes. (AI)
75	Knows how to monitor public spending of local and national government (e.g. through open data on the government's website and open data portals).
76	Knows how to identify areas where AI can bring benefits to various aspects of everyday life. For example, in healthcare, AI might contribute to early diagnosis, while in agriculture, it might be used to detect pest infestations. (AI)
79	Readiness to contemplate ethical questions related to AI systems (e.g. in which contexts, such as sentencing criminals, should AI recommendations not be used without human intervention)? (AI)
2.4 Collaborating through Digital Technologies	
	No entries
2.5 Netiquette	
	No entries
2.6 Managing Digital Identity	
104	Aware that digital identity refers to (1) the method of authenticating a user on a website or an online service, and also to (2) a set of data identifying a user by means of tracing their digital activities, actions and contributions on the internet or digital devices (e.g. pages viewed, purchase history), personal data (e.g. name, username, profile data such as age, gender, hobbies) and context data (e.g. geographical location).
105	Aware that AI systems collect and process multiple types of user data (e.g. personal data, behavioural data and contextual data) to create user profiles which are then used, for example, to predict what the user might want to see or do next (e.g. offer advertisements, recommendations, services). (AI)
106	Knows that in the EU, one has the right to ask a website's or search engine's administrators to access personal data held about you (right of access), to update or correct them (right of rectification), or remove them (right of erasure, also known as the Right To Be Forgotten).
111	Able to verify and modify what type of metadata (e.g. location, time) is included in pictures being shared in order to protect privacy.
112	Knows what strategies to use in order to control, manage or delete data that is collected/curated by online systems (e.g. keeping track of services used, listing online accounts, deleting accounts that are not in use).
113	Knows how to modify user configurations (e.g. in apps, software, digital platforms) to enable, prevent or moderate the AI system tracking, collecting or analysing data (e.g. not allowing the mobile phone to track the user's location). (AI)
114	Considers the benefits (e.g. fast authentication process, user preferences) and risks (e.g. having identities stolen, personal data exploited by third parties) when managing one or multiple digital identities across digital systems, apps and services.
117	Identifies both the positive and negative implications of the use of all data (collection, encoding and processing), but especially personal data, by AI-driven digital technologies such as apps and online services. (AI)
3. Digital Content Creation	

(*continued*)

3.1 Develop Digital Content	
119	**Knows that AI systems can be used to automatically create digital content (e.g. texts, news, essays, tweets, music, images) using existing digital content as its source. Such content may be difficult to distinguish from human creations. (AI)**
122	**Can use tools and techniques to create accessible digital content (e.g. add ALT text to images, tables and graphs; create a proper and well-labelled document structure; use accessible fonts, colours, links) following official standards and guidelines (e.g. WCAG 2.1 and EN 301 549). (DA)**
124	**Knows how to create digital content to support one's own ideas and opinions (e.g. to produce data representations such as interactive visualisations using basic datasets such as open government data).**
127	**Inclined to combine various types of digital content and data to better express facts or opinions for personal and professional use.**
3.2 Integrating and Re-elaborating Digital Content	
130	Aware that it is possible to integrate hardware (e.g. sensors, cables, motors) and software structures to develop programmable robots and other non-digital artefacts (e.g. Lego Mindstorms, Micro:bit, Raspberry Pi, EV3, Arduino, ROS).
131	Can create infographics and posters combining information, statistical content and visuals using available apps or software
133	**Knows how to integrate digital technologies, hardware and sensor data to create a new (digital or non-digital) artefact (e.g. makerspace and digital fabrication activities).**
134	Knows how to incorporate AI edited/manipulated digital content in one's own work (e.g. incorporate AI generated melodies in one's own musical composition). This use of AI can be controversial as it raises questions about the role of AI in artworks, and for example, who should be credited
3.3 Copyright and Licences	
	No entries
3.4 Programming	
154	**Knows that programs produce output data depending on input data, and that different inputs usually yield different outputs (e.g. a calculator will provide output 8 to the 3+5 input and output 15 to the 7+8 input).**
155	**Knows that, to produce its output, a program stores and manipulates data in the computer system that executes it, and that it sometimes behaves unexpectedly (e.g. faulty behaviour, malfunction, data leakage).**
156	Knows that a program's blueprint is based on an algorithm, i.e. a step-wise method to produce an output from an input.
157	**Knows that algorithms, and consequently programs, are designed to help solve real life problems; input data models the known information about the problem, while output data provides information relevant to the problem's solution. There are different algorithms, and consequently programs, solving the same problem.**
159	Knows that there are problems that cannot be solved exactly by any known algorithm in reasonable time, thus, in practice they are frequently dealt with by approximate solutions (e.g. DNA sequencing, data clustering, weather forecasting).
162	Able to identify input and output data in some simple programs.
164	**Willing to accept that algorithms, and hence programs, may not be perfect in solving the problem that they aim to address.**
165	Considers ethics (including but not limited to human agency and oversight, transparency, non-discrimination, accessibility, and biases and fairness) as one of the core pillars when developing or deploying AI systems. (AI)
4. Safety	
4.1 Protecting Devices	
167	Knows about measures to protect devices (e.g. password, fingerprints, encryption) and prevent others (e.g. a thief, commercial organisation, government agency) from having access to all data.

(*continued*)

170	Aware of different types of risks in digital environments, such as identity theft (e.g. someone committing fraud or other crimes using another person's personal data), scams (e.g. financial scams where victims are tricked into sending money), malware attacks (e.g. ransomware).
172	Knows how to install and activate protection software and services (e.g. antivirus, anti-malware, firewall) to keep digital content and personal data safer.
174	Knows how to check the type of personal data an app accesses on one's mobile phone and, based on that, decides whether to install it and configures the appropriate settings
175	Able to encrypt sensitive data stored on a personal device or in a cloud storage service
176	Can respond appropriately to a security breach (i.e. an incident that results in unauthorised access to digital data, applications, networks or devices, the leaking of personal data such as logins or passwords).
4.2 Protecting Personal Data and Privacy	
180	Aware that secure electronic identification is a key feature designed to enable safer sharing of personal data with third parties when conducting public sector and private transactions.
181	Knows that the "privacy policy" of an app or service should explain what personal data it collects (e.g. name, brand of device, geolocation of the user), and whether data are shared with third parties.
182	Knows that the processing of personal data is subject to local regulations such as the EU's General Data Protection Regulation (GDPR) (e.g. voice interactions with a virtual assistant are personal data in terms of the GDPR and can expose users to certain data protection, privacy and security risks). (AI)
183	Knows how to identify suspicious e-mail messages that try to obtain sensitive information (e.g. personal data, banking identification) or might contain malware. Knows that these emails are often designed to trick people who do not check carefully and who are thus more susceptible to fraud, by containing deliberate errors that prevent vigilant people clicking on them.
187	Weighs the benefits and risks before allowing third parties to process personal data (e.g. recognises that a voice assistant on a smartphone, that is used to give commands to a robot vacuum cleaner, could give third parties - companies, governments, cybercriminals – access to the data). (AI)
4.3 Protecting Health and Wellbeing	
	No entries
4.4 Protecting the Environment	
203	Aware of the environmental impact of everyday digital practices (e.g. video streaming that rely on data transfer), and that the impact is composed of energy use and carbon emissions from devices, network infrastructure and data centres.
208	**Aware that digital technologies (including AI-driven ones) can contribute to energy efficiency, for example through monitoring the need for heating at home and optimising its management.**
209	Aware that certain activities (e.g. training AI and producing cryptocurrencies like Bitcoin) are resource intensive processes in terms of data and computing power. Therefore, energy consumption can be high which can also have a high environmental impact. (AI)
216	Considers the ethical consequences of AI systems throughout their life-cycle: they include both the environmental impact (environmental consequences of the production of digital devices and services) and societal impact, e.g. platformisation of work and algorithmic management that may repress workers' privacy or rights; the use of low-cost labour for labelling images to train AI systems. (AI)
5. Problem Solving	
5.1 Solving Technical Problems	
221	Aware that AI is a product of human intelligence and decision-making (i.e. humans choose, clean and encode the data, they design the algorithms, train the models, and curate and apply human values to the outputs) and therefore does not exist independently of humans. (AI)
5.2 Identify Needs and Technological Responses	

(continued)

228	Able to identify some examples of AI systems: product recommenders (e.g. on online shopping sites), voice recognition (e.g. by virtual assistants), image recognition (e.g. for detecting tumours in x-rays) and facial recognition (e.g. in surveillance systems). (AI)
231	Aware that AI-driven speech-based technology enables the use of spoken commands that can enhance the accessibility of digital tools and devices (e.g. for those with mobility or visual limitations, limited cognition, language or learning difficulties), however, languages spoken by smaller populations are often not available, or perform worse, due to commercial prioritisation. (AI) (DA)
233	Knows how and when to use machine translation solutions (e.g. Google Translate, DeepL) and simultaneous interpretation apps (e.g. iTranslate) to get a rough understanding of a document or conversation. However, also knows that when the content requires an accurate translation (e.g. in healthcare, commerce or diplomacy), a more precise translation may be needed. (AI)
5.3 Creatively Using Digital Technology	
246	Open to engage in collaborative processes to co-design and co-create new products and services based on AI systems to support and enhance citizens' participation in society. (AI)
5.4 Identifying Digital Competence Gaps	
251	Aware that AI is a constantly-evolving field, whose development and impact is still very unclear. (AI)
255	Has a disposition to keep learning, to educate oneself and stay informed about AI (e.g. to understand how AI algorithms work; to understand how automatic decision-making can be biased; to distinguish between realistic and unrealistic AI; and to understand the difference between Artificial Narrow Intelligence, i.e. today's AI capable of narrow tasks such as game playing, and Artificial General Intelligence, i.e. AI that surpasses human intelligence, which still remains science fiction). (AI)

Appendix 1B: DigComp 2.2 Coding on DLCM									
	Coding on Data Literacy Competence Model								
	Using Data					Understanding Data			
	Interpreting	Navigating	Collecting	Processing	Presenting	Observing	Analysing	Evaluating	Reflecting
1. Information and Data Literacy									
1.1 Browsing, Searching and Filtering Data, Information and Digital Content									
2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
4	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
5	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
8	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
9	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
12	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
14	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
1.2 Evaluating Data, Information and Digital Content									
18	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
19	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
20	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
21	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
22	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
27	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
1.3 Managing Data, Information and Digital Content									
31	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
32	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
33	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
34	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
35	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
36	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
37	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
38	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
39	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
40	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
41	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
42	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
2. Communication and Collaboration									
2.1 Interacting through Digital Technologies									
43	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
50	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
51	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

(continued)

54	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
2.2 Sharing through Digital Technologies									
56	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
59	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
2.3 Engaging Citizenship through Digital Technologies									
67	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
69	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
70	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
71	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
75	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
76	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
79	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
2.4 Collaborating through Digital Technologies									
2.5 Netiquette									
2.6 Managing Digital Identity									
104	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
105	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
106	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
111	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
112	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
113	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
114	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
117	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
3. Digital Content Creation									
3.1 Develop Digital Content									
119	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
122	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
124	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
127	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
3.2 Integrating and Re-elaborating Digital Content									
130	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
131	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
133	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
134	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
3.3 Copyright and Licences									
3.4 Programming									
154	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
155	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
156	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE

(*continued*)

157	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
159	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
162	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
164	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
165	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
4. Safety									
4.1 Protecting Devices									
167	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
170	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
172	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
174	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
175	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
176	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
4.2 Protecting Personal Data and Privacy									
180	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
181	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
182	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
183	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
187	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
4.3 Protecting Health and Wellbeing									
4.4 Protecting the Environment									
203	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
208	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
209	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
216	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
5. Problem Solving									
5.1 Solving Technical Problems									
221	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
5.2 Identify Needs and Technological Responses									
228	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
231	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
233	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
5.3 Creatively Using Digital Technology									
246	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
5.4 Identifying Digital Competence Gaps									
251	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
255	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
	3	7	1	9	11	18	9	16	10
Overall totals	31					53			

Appendix 1C: DigComp 2.2 Coding Thematically

	Thematic Coding														
	Data								Artificial Intelligence						
	Understanding Data	Problem Solving	Security	Identity, Privacy & Ethics	Representation of Data	Transparency	Environmental Impact	Citizenship	Understanding AI	Identity, Privacy & Ethics	Recommender Systems	Search	Bias In Algorithms	Environmental Impact	Citizenship
1. Information and Data Literacy															
1.1 Browsing, Searching and Filtering Data, Information and Digital Content															
2	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
4	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
5	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
8	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
9	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
12	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
14	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
1.2 Evaluating Data, Information and Digital Content															
18	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
19	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
20	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
21	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
22	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
27	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
1.3 Managing Data, Information and Digital Content															
31	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
32	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
33	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
34	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
35	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
36	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
37	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
38	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
39	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
40	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
41	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
42	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2. Communication and Collaboration															
2.1 Interacting through Digital Technologies															
43	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
50	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
51	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
54	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
2.2 Sharing through Digital Technologies															
56	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
59	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2.3 Engaging Citizenship through Digital Technologies															
67	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
69	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
70	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
71	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
75	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
76	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
79	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE

(continued)

2.4 Collaborating through Digital Technologies															
2.5 Netiquette															
2.6 Managing Digital Identity															
104	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
105	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
106	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
111	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
112	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
113	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
114	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
117	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
3. Digital Content Creation															
3.1 Develop Digital Content															
119	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
122	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
124	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
127	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
3.2 Integrating and Re-elaborating Digital Content															
130	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
131	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
133	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
134	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
3.3 Copyright and Licences															
3.4 Programming															
154	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
155	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
156	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
157	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
159	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
162	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
164	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
165	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
4. Safety															
4.1 Protecting Devices															
167	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
170	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
172	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
174	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
175	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
176	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
4.2 Protecting Personal Data and Privacy															
180	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
181	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
182	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
183	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
187	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
4.3 Protecting Health and Wellbeing															
4.4 Protecting the Environment															

(*continued*)

203	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
208	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
209	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
216	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
5. Problem Solving															
5.1 Solving Technical Problems															
221	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
5.2 Identify Needs and Technological Responses															
228	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
231	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
233	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
5.3 Creatively Using Digital Technology															
246	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
5.4 Identifying Digital Competence Gaps															
251	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
255	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
	3	4	8	12	14	5	2	2	5	12	2	2	8	3	3
Overall totals	50								35						

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