13. DATA REUSE: FAIR PRINCIPLES AND THE RESEARCH ECOSYSTEM

Sônia Elisa Caregnato[155]
Rafael Port da Rocha[156]
Rene Faustino Gabriel Junior[157]

13.1 INTRODUCTION

The Open Science movement has gained momentum recently due to both technological advancement and society's perception that scientific research is a collective activity, publicly funded, and that needs to return value to the society that supports it.

In this matter, data produced in the course of a research, in addition to publications that contextualized them, must be in open access so they can be shared among scientists and reused in new research, providing feedback to science, whose character is cumulative. Therefore, data sharing has been a demand of governments, funding agencies and research institutions, but in order for this to materialize, planning, management and curation of data sets in repositories are necessary. Such activities occur in the scope of a research ecosystem that involves technologies, people, and institutions.

With the aim of ensuring good practices for research data sharing, FAIR principles establish that data should be findable, accessible, interoperable, and reusable. The intention is, through the principles, to facilitate data reuse both by humans and machines. (Wilkson *et al*., 2016).

Therefore, sharing and reuse represent a pair of concepts that complement each other. However, as observed by some authors (Pasquetto; Randles; Borgman, 2017; Tenopir *et al*., 2011; Wallis *et al*., 2013), the first is much more frequently studied than the second, although the benefits of sharing can only be obtained if data are effectively reused.

Searching for a deeper understanding of this subject and its implications, this paper explores the use of the term research data *reuse*, as well as terms commonly related to it, through a literature review. Initially, research data sharing is approached, then it is related to reuse and FAIR principles. Afterward, the meaning of the terms

155 PhD by the University of Sheffield, United Kingdom. Professor in Graduate Programs in Communication and Information Science, both at the Federal University of Rio Grande do Sul (UFRGS). Email: sonia.caregnato@ufrgs.br

156 PhD in Computer Science by the Federal University of Rio Grande do Sul (UFRGS). Professor in Graduate Program in Information Science UFRGS. Email: rafael.rocha@ufrgs.br

157 PhD in Computer Science by Paulista Júlio de Mesquita Filho State University

(Unesp). Professor in the Graduate Program in Information Science at the Federal University of Rio Grande do Sul (UFRGS). Email: rene.gabriel@ufrgs.br

use and *reuse* is discussed, as well as their variations to, finally, address the necessary conditions for an effective reuse of research data.

13.2 RESEARCH DATA SHARING

Research data sharing is intrinsically related to its use, whether to validate it or originate new interpretations. However, the sharing act informs very little about the use that will be made of data. There is, indeed, an assumption in the open access policies, that is, that research data are useful for other researchers and that they are going to reuse them (Pasquetto *et al*., 2019).

According to Borgman (2012), sharing concerns the act of opening data in a way they can be reused by other individuals. It is important to point out that the degree of confidence, the use, and the value of these data vary dramatically: while some are structured and curated, others are simply made available.

In part, at least, the quality of data made available depends on how it is shared. Pasquetto, Randles e Borgman (2017) specify that sharing can be done through private exchanges between researchers, deposit in repositories, availability in lab websites, supplement of journal articles and, more recently, data articles, which clarify the provenance and enable the allocation of credit to authors. Thus, for the authors, both direct exchanges between researchers and the open availability of data are understood as sharing. The way it is done, according to the authors, varies in relation to the knowledge area, data type, country, funding agency and other factors.

Boté and Térmens (2019), on the other hand, prefer to differentiate private sharing from public sharing in general or specialized institutional repositories, calling the latter publication. For them, sharing among peers during the period when data is not necessarily publicly available assumes a high level of trust between the parties, as well as an easier way to obtain information through informal channels on how to integrate data in new projects. Data release in repositories, however, demands a greater effort given the need to provide detailed documentation that accompanies data and explain how to use them.

Regardless of the way, there are, evidently, advantages to data sharing. Borgman (2012) identified four rationales for this practice. They are: a) to reproduce or to verify results; b) to make available the results of the research funded by the public sector; c) to enable others to formulate new research questions based on existing data; d) to advance research and innovation.

However, there are also barriers and challenges to data sharing. So much that, as it is an intricate and complex phenomenon, Professor Christine Borgman called it a conundrum in her famous 2012 article. According to her,

> If the rewards of the data deluge are to be reaped, then researchers who produce those data must share them, and do so in such a way that the data is interpretable and reusable by others. Underlying this simple statement are thick layers of complexity about the nature of data, research, innovation, and scholarship, incentives and rewards, economics and intellectual property, and public policy (Borgman, 2012, p. 1.059).

Among the difficulties for not sharing research data are fears of inappropriate use of data and competition, the cost of preparing data and documentation, lack of time, lack of appropriate infrastructure and standards, ethical issues – among them, the use of data for purposes apart from those for which they were collected – and, finally, the fact that raw data are of little use for reuse without significant efforts to make them available in a way that allows further analysis (Borgman, 2012; Kim; Yonn, 2017; Perrier *et al*., 2020; Rowley *et al*., 2017; Tenopir *et al*., 2011; Wallis; Rolando; Borgman, 2013).

The support for research data sharing and the struggle to overcome obstacles to data reuse motivate the search for measures to guide the necessary management actions. FAIR principles are an important milestone in this effort and also in expanding the value of data for its reuse, as will be discussed below.

13.3 FAIR PRINCIPLES AND THE RESEARCH ECOSYSTEM

In addition to being one of the four FAIR principles, reuse is also the purpose of data curation processes. The main feature of FAIR principles is the provision of a concise, high-level set of guidelines that are valid for any domain and that must be applied not only to data, but also to metadata. Accordingly, they present themselves as a means of facilitating reuse.

In a final report entitled Turning FAIR into reality (Collins *et al*., 2018), The European Commission's FAIR Data Specialist Group pointed out that the implementation of principles requires the creation of a new research culture, in addition to a technical ecosystem consisting of appropriate services and infrastructure, which include policies, data management plans, persistent identifiers, interoperability standards, metadata, and repositories. In addition, the authors stress that it is necessary to promote the development of skills to, on the one hand, process and analyze data (data science), and on the other hand, manage and preserve them throughout their life cycle (data curation). It is also necessary to develop indicators for evaluating compliance with the Principles and, ultimately, pursue project sustainability and funding.

The report defines the FAIR ecosystem as a model that indicates the minimum components necessary to promote the creation, curation, and reuse of FAIR digital objects in an effective and sustainable way (Collins *et al*., 2018). The central element of this ecosystem, therefore, is the digital object (research data and other resources), which must be accompanied of persistent identifiers and metadata to enable it to be found, used and cited. FAIR digital objects also need to be represented, ideally in open file formats and use vocabulary common to communities, so that interoperability and reuse are possible. In addition, the associated documentation must include machine-actionable instructions on conditions of use and licensing. Finally, as pointed out by Koers *et al*. (2020), this ecosystem is supported by metrics, certification mechanisms, incentives, funding and training.

An important movement for FAIR principles to become effective is the GO FAIR initiative, which emerged in Europe in 2017, and expanded to other countries including Brazil. GO FAIR proposes the formation of networks for implementing FAIR data and services, so that those interested can work in participative and collaborative ways (Sales *et al*., 2020).

Neither FAIR principles nor GO FAIR initiatives establish the obligation for all research data to be open, that is, data can be FAIR and, at the same time, be shared in a restricted way. This provision is necessary in certain circumstances, for example when including personal, confidential or commercially valuable information. The greatest benefits to science and society, however, occur when data are both FAIR and open, as the absence of restrictions increases the possibilities of large-scale reuse (Collins *et al*., 2018), or, as claimed by Henning *et al.* (2019, p. 394),

> [...] the more open they are, the more they will be used, reused and combined with other data, promoting economic growth, innovation, and development... Information on use licenses, however, must be clearly specified for the data to be considered FAIR. Thus, if the data cannot be opened, or if they can only be used with restrictions, this information must be made explicit.

The FAIR principles establish that (Wilkinson *et al*., 2016):

> R1. meta (data) are richly described with a plurality of accurate and relevant attributes
> R1.1. (meta)data are released with a clear and accessible data usage license
> R1.2. (meta)data are associated with detailed provenance
> R1.3. (meta)data meet domain-relevant community standards

That is, to be reused, both data and metadata must be accompanied of information that effectively enables them to be used in different contexts from those to which they were created.

In this matter, Turning FAIR into reality report (Collins *et al*., 2018) suggests 27 recommendations, each one accompanied by a set of relevant actions set to support the realization of FAIR data ecosystem. Among these, there are some directly related to the reuse. Particularly, the authors recommend that research funders should encourage FAIR data reuse, requiring that communities approach existing content whenever possible. This can be done by requiring researchers to show in their projects that FAIR data were searched and/or looked into before proposing the creation of new data, or when acknowledging that the results from research that reused data has the same value of research that created new content, or when financing research that reuse FAIR data.

For reuse to effectively derive from sharing, it is necessary to understand all dimensions of the phenomenon, starting with the definition of the term itself. Thus, the next section deals specifically with the reuse of data, considering its dimensions and characteristics.

13.4 RESEARCH DATA REUSE

As previously mentioned, research data sharing implies its reuse for of science itself, the scientific community and society in general, that is, from the perspective of the research ecosystem. In this regard, it is initially necessary to clarify the meaning of reuse in this specific context and in its relation to the use of research data.

According to Van de Sandt and colleagues (2019), the term *research data reuse* refers to a complex concept that varies according to the knowledge areas. Even so, the authors stress that it is essential to define it because it has been increasingly used by funding and research institutions, showing its importance.

The first distinction frequently found is that between use and reuse, as suggested by Pasquetto, Borgman, Wofford and Pasquetto (2017), Randles and Borgman (2019). Other related concepts are also pointed out in the literature, for example, reproducibility, replicability, integration, and reanalysis (Boté; Térmens, 2019; Curty, 2019;

Van de Sandt, 2019). These aspects, including taxonomy proposals or models to understand data types, will be discussed below.

13.4.1 Defining reuse

Reuse is often defined as the subsequent use, made by other researchers, of data collected for a certain project, or as precisely stated by Boté and Térmens (2019, p. 329), "[...] finding, processing and analyzing someone else's datasets to create new knowledge".

Three elements are essential in this definition: a) it is a secondary use, not originally intended; b) it happens temporally after use; and c) it is done by a researcher or research group different from the one who collected data. Regarding the first and second aspects, there appears to be no divergence in the literature. In relation to the third, however, there are divisions. Pasquetto, Borgman and Wofford (2017) explicitly point out that, if the same scientist returns to the same dataset in a later project, this action would be characterized as use and not reuse. For the authors, reuse occurs when datasets are retrieved by third parties and used in another project. Some authors, however, do not establish this distinction, for example, Custers and Uršič (2016), while others still defend that any subsequent use, even if it is by whom collected the data, must be considered reuse (Curty, 2019).

A distinctive approach is that taken by Van de Sandt and colleagues (2019), who concluded that the discourse characteristics of the subject area do not prove that there is any difference between reuse and use. Based on the etymological analysis of the words *use* and *reuse* and on related concepts, as well as on discourse analysis and the formulation of scenarios, the authors consider four characteristics frequently used to differentiate use from reuse

> a) the character of the data, which refers to the number of reused datasets or their transformation by reuse;
> b) the user, who the literature differentiates from the data producer;
> c) the purpose, which is related to the research question and/or method;
> d) the temporal dimension, in which the original use is evidenced before the second use of the data.

Based on these analyses, authors state: "Therefore, we define (re)use as the use of any research resource, regardless of when it is used, its purpose, its characteristics and its user" (Van de Sandt *et al*., 2019, p. 14). Furthermore, they seek to credit the confusion of terms to the linear model centered on the published article, which would be less dynamic and complex than the current research scenario.

The originality of the work is also in relating this proposal of simplifying the language to the involvement in the open science movement, since, according to the authors, researchers would be more likely to publish and document quality research for a purpose (the use) that is already consolidated, instead of a different purpose (reuse) that is not clearly understood (Van de Sandt *et al*., 2019). A more detailed analysis of the article, however, could reveal that this is a strategy related to the perception that peer recognition is greater when it comes to original work (use) rather than secondary (reuse). This could be manifested in the author's concern about evaluating the impact of research through citations, which is also mentioned in the text.

In any case, much of the literature that addresses the topic does not seem prone to such a change, at least in the short term. Therefore, it is understood that this differentiation will continue, mainly because it is useful in the context of privacy and data protection, as will be discussed later. Next, taxonomies or models that seek to differentiate the ways in which data are reused are discussed.

13.4.2 Types of data reuse

Reuse can be understood as a broader category, which encompasses reproducibility, replicability, reuse, integration and reanalysis, among other terms (Curty, 2019; Pasquetto; Randles; Borgman, 2017; Van de Sandt *et al*., 2019).

Starting from the context of *big data* and not of research data, but without excluding them, after identifying practical, technological and legal barriers, Custers and Uršič (2016) propose a reuse taxonomy composed of three elements: recycling, repurposing and recontextualization. Data recycling refers to using data several times, but always with the same initial purpose; data repurposing refers to reusing data for distinct purposes for which they were primarily collected; and data recontextualization implies using data in different contexts from the ones they were initially obtained. This distinction is particularly important from a legal perspective, in situations that involve privacy and protection of personal data, as normally the research subjects' authorization to use the data is given on the condition that its use is made only within the scope of that study.

Pasquetto, Randles and Borgman (2017), based on previous literature, differentiate reproducibility from replication, on one hand, and integration from independent reuse, on the other hand. Reproducibility occurs when a research problem is formulated again based on the same data and methods, to validate, verify or confirm the research, whereas replication implies the use of new data to answer, with the same methods, a previous question. The independent reuse refers to an external agent that performs the reuse; for example, the reproduction of a study is an example of independent reuse. Integration involves the reuse of datasets combined with other data, whether they are the result of research by others or of new observations.

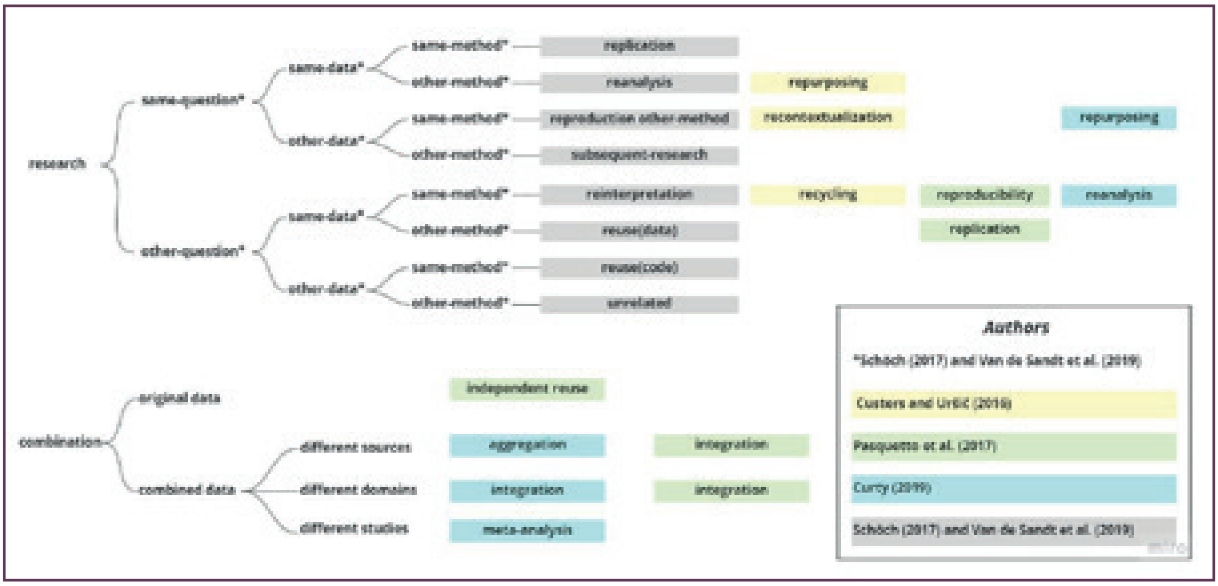
As can be seen, these are not excluding dimensions or that can be easily distinguished from each Other. Thus, in a later study, Pasquetto, Borgman and Wofford (2019) introduce another type of differentiation: reuse is a continuum that ranges from comparative to integrative. Comparative data reuse, as the term implies, involves using data for a specific comparison, which requires interaction experience, that is, knowing enough about the data to assess its quality and value. On the other hand, integrative reuse, such as using data in a new experiment, involves interpretation and, therefore, requires more specialized and in-depth scientific knowledge to be carried out, as well as greater confidence in the quality of data to be reused

Curty (2019) proposes a classification that describes five approaches for research data reuse, as follows, a) repurposing; b) aggregation; c) integration; d) metanalysis; and e) reanalysis. According to the author, in repurposing, data from a single study is fully or partially reused for new analysis, resulting from different research questions, without being complemented or integrated with data from other sources. In reuse by aggregation, data from different studies/sources are gathered to compose a more complete dataset. The reuse by integration is the one that combines data from different types of studies, through variables that connect separate studies. The metanalysis combines data from multiple independent studies, with very similar research questions, integrating them into a broader and more substantial analysis. The reanalysis involves the verification of original results, through new analysis, using the same methods and techniques, that is, it is the concept of reproducibility approached by Pasquetto, Randles and Borgman (2017).

As can be seen, there is no consensus among researchers on a definition for reuse or even on how to categorize its variables and specificities. An approach that seems promising for systematizing the different concepts of reuse based on three dimensions of research (question, data, and method), is that of Schöch (2017). The author derives eight categories of reproducibility in research, two of which (subsequent research and unrelated research) are not types of reuse, unlike the six others, which are directly related to reuse, namely: replication, reanalysis, reproducibility, reinterpretation, data reuse and code reuse.

To relate these different concepts used in the literature, it is proposed to group Custers and Uršič's (2016), PPasquetto, Randles and Borgman's (2017), Curty 's(2019) and Schöch's (2017) and Van de Sandt 's(2019) classifications (Figure 1). This grouping occurs based on the observation of two general criteria: types of reuse determined by the research context and types of reuse determined by the need to combine data. The types of reuse determined by research context are regrouped based on categories proposed by Schöch (2017) and Van de Sandt (2019): same/other research questions, same/other data and same/other research methods.

Figure 1 – Categorization of term related to the concept of research data reuse



Source: authors.

Figure 1 also shows that "repurposing", "recycling", and "recontextualization" by Custers and Uršič (2016), "reproducibility" and "replication" by Pasquetto, Randles and Borgman (2017), and "repurposing" and "reanalysis" by Curty (2019), assign data reuse to the research context. The combination of data with others is a criterion for "integration", "aggregation" and "meta-analysis", by Curty (2019), and "independent reuse" and "integration", by Pasquetto, Randles and Borgman (2017). Interestingly, in Schöch (2017) and Van de Sandt (2019), there is an inversion between term and concept, about "replication" and "reproducibility", in relation to Pasquetto, Randles and Borgman (2017).

It is understood that the representation synthesizes the interpretations of the term reused in the literature about research data, while revealing the complexity of the initiatives to understand it effectively

13.4.3 Conditions for research data reuse

Conceptual definitions are essential, but the effective reuse of research data can only occur if conditions are offered to researchers and appropriate actions encouraged in the scope of research ecosystem.

In a study to evaluate the practices of research data reuse in situations in which such use failed, Yoon (2016) proposed ways of overcoming the problems. The author offers the following suggestions:

> a) ease of reusing, particularly related to the interoperability and access, is an initial condition for successful experiences with data reuse;
> b) understanding data through documentation can be a minor difficulty, at least for experienced researchers, although the process still represents a challenge;
> c) the main component of reuse experience that becomes flawed is the lack of support for data reuse, which shows the need to develop a supporting system for those who reuse research data.

The importance of documentation is frequently emphasized as an essential condition for a successful reuse. For instance, Curty (2019) discusses that to be reused, data needs to be considered relevant, complete, understandable and reliable, and that these attributes can only be observed if data are accompanied by supplementary information and descriptions about its origin and processing, that is, documentation contextualizing them. Although it is not exactly Yoon's (2016) results, the Curty (2019) points out the need to develop data reuse skills. This is also stressed by Estevão and Strauhs' (2020) work, which points to the requirement of informational literacy in data reuse by researchers, many of whom have no experience in the subject.

The results of the study by Kim and Yoon (2017) on the data reuse behavior of scientists show that there are significant variations between disciplines, as well as within them, in data reuse intentions. The usefulness of data, as perceived by scientists, the concern with their quality and the offer of resources in their organizations were considered the most important elements by interviewees for the reuse of data. At the disciplinary level, the availability of data repositories showed a significant positive relationship with the intention to reuse data.

In summary, for the reuse of research data to materialize and for it to fulfill the promise of improving the form and results of knowledge production for of society as a whole, it is necessary to mobilize the entire research ecosystem: people need incentives and training; institutions need to provide the necessary conditions and technologies must be exploited to their full potential.

13.5 FINAL CONSIDERATIONS

Data reuse is the centerpiece of the research ecosystem, and the benefits of data will only be effective if data are prepared with reuse as a principle, as when adopting FAIR principles. Reuse is also one of the goals of digital curation of research data, as it comprises actions that will maintain and add value to reliable data for present and future use. Furthermore, the values of this data can only be determined through a proper understanding of its reuse, in the context of its user community.

The term *research data reuse* refers to a complex concept. To help researchers or data curators to understand data reuse, this work aimed at developing an analysis of this term through its definitions, its relationship with other terms and characteristics that provide distinctions between use and reuse. It also approached ways of reuse, through identification of its types, categories, and benefits.

Further studies on reuse are necessary, as is the understanding of the perspectives and practices of researchers from different scientific communities since research data reuse will not be fully achieved through the simple availability of data in repositories. There is an ecosystem that needs to be mobilized to make it possible to achieve this end.

REFERENCES

BERGHMANS, S. *et al*. Open Data: the researcher perspective - survey and case studies, 2017. **Mendeley Data**, v. 1, 4 apr. 2017. DOI: 10.17632/bwrnfb4bvh.1

BORGMAN, C. L.; SCHARNHORST, A.; GOLSHAN, M. S. Digital data archives as knowledge infrastructures: mediating data sharing and reuse. **Journal of the Association for Information Science and Technology**, v. 70, n. 8, p. 888–904, 2019.

BORGMAN, C. L. The conundrum of sharing research data. **Journal of the American Society for Information Science and Technology**, v. 63, n. 6, p. 1059–1078, 2012. DOI: 10.1002/asi.22634

BOTÉ, J.; TÉRMENS, M. Reusing Data: Technical and Ethical Challenges. **DESIDOC Journal of Library & Information Technology**, v. 39, n. 6, p. 329-337, 2019. DOI: 10.14429/djlit.39.6.14807

COLLINS, S.; *et al*. **Turning FAIR into reality**: final report and action plan from the European Commission expert group on FAIR data. Bruxelas: European Commission, 2018. DOI: 10.2777/1524.

CURTY, R. G. Abordagens de reúso e a questão da reusabilidade dos dados científicos. **Liinc em revista**, v. 15, n. 2, 2019. DOI: 10.18617/liinc.v15i2.4777

CUSTERS, B.; URŠIČ, H. Big data and data reuse: a taxonomy of data reuse for balancing big data benefits and personal data protection. **International Data Privacy Law**, v. 6, n. 1, p. 4–15, 2016. DOI: 10.1093/idpl/ipv028.

DIAS, G. A.; ANJOS, R. L. D.; ARAÚJO, D. G. A, Gestão dos dados de pesquisa no âmbito da comunidade dos pesquisadores vinculados aos programas de pós-graduação brasileiros na área da ciência da informação: desvendando as práticas e percepções associadas ao uso e reúso de dados. **Liinc em revista**, v. 15, n. 2, 2019. DOI: 10.18617/liinc.v15i2.4683

ESTEVÃO, J. S. B.; STRAUHS, F. R. Letramento informacional para reúso de dados nas ciências sociais: requisitos e competências. **Informação & Informação**, v. 25, n. 2, p. 1-25, 2020. DOI: 10.5433/1981-8920.2020v25n2p1

HENNING, P. C. *et al*. GO FAIR e os princípios FAIR: o que representam para a expansão dos dados de pesquisa no âmbito da Ciência Aberta. **Em Questão**, v. 25, n. 2, p. 389-412, maio/ago. 2019. DOI: http://dx.doi.org/10.19132/1808-5245252.389-412

KIM, Y.; YOON, A. Scientists' data reuse behaviors: a multilevel analysis. **Journal of the Association for Information Science and Technology**, v. 68, n. 12, p. 2709-2719, 2017. DOI: 10.1002/asi.23892

KOERS, H. *et al*. Recommendations for Services in a FAIR Data Ecosystem. **Patterns**, v. 1, n. 5, 100058, 2020. DOI: 10.1016/j.patter.2020.100058

PASQUETTO, I. V.; BORGMAN, C. L.; WOFFORD, M. F. Uses and Reuses of Scientific Data: The Data Creators' Advantage. **Harvard Data Science Review**, v. 1, n. 2, 2019. DOI: 10.1162/99608f92.fc14bf2d

PASQUETTO, I. V.; RANDLES, B. M.; BORGMAN, C. L. On the reuse of scientific data. **Data Science Journal**, v. 16, n. 8, 2017. DOI: 10.5334/dsj-2017-008

PERRIER, L; BLONDAL, E.; MACDONALD, H. The views, perspectives, and experiences of academic researchers with data sharing and reuse: A meta-synthesis. **PLoS ONE**, v. 15, n. 2, e0229182, 2020. DOI: 10.1371/journal.pone.0229182

ROWLEY, J. *et al*. Academics' behaviors and attitudes towards open access publishing in scholarly journals. **Journal of the Association for Information Science and Technology**, v. 68, n. 5, p. 1201-1211, 2017. DOI: https://doi.org/10.1002/asi.23710.

SALES, L. *et al*. GO FAIR Brazil: a challenge for Brazilian data science. **Data Intelligence**, v. 2, n. 1-2, p. 238-245, 2020. DOI: 10.1162/dint_a_00046

SCHÖCH, C. Wiederholende Forschung in den digitalen Geisteswissenschaften. In: Digital Nachhaltigkeit, 2017, Bern, Switzerland. **Proceedings [...]** Bern: Universitat Bern, 2017. p. 13-18. Available from: https://zenodo.org/record/277113#.X6D7u4hKi01 Access on: 14 out. 2020

TENOPIR, C. *et al*. Data sharing by scientists: practices and perceptions. PLoS ONE, San Francisco, v. 6, n. 6, e21101, 2011. DOI: 10.1371/journal.pone.0021101

VAN DE SANDT, T. *et al*. The definition of reuse. **Data Science Journal**, v. 18, n. 1, p. 1-19, 2019. DOI: https://doi.org/10.5334/dsj-2019-022

WALLIS, J.C.; ROLANDO, E.; BORGMAN, C.L. If We Share Data, Will Anyone Use Them? Data Sharing and Reuse in the Long Tail of Science and Technology**. PLoS ONE**, v. 8, n. 7, e67332, 2013. DOI: 10.1371/journal.pone.0067332

WILKINSON, M. D. et al. The FAIR Guiding Principles for scientific data management and stewardship. **Scientific Data**, v. 3, n. 160018, mar. 2016.

YOON, A. Red flags in data: Learning from failed data reuse experiences. **Proceedings of the Association for Information Science and Technology**, v. 53, n. 1, p. 1–6, 2016. DOI: https://doi.org/10.1002/pra2.2016.14505301126

How to cite this chapter: CAREGNATO, Sônia Elisa; ROCHA, Rafael Port da; GABRIEL JUNIOR, Rene Faustino. Data reuse: FAIR principles and the research ecosystem. *In*: SALES, Luana Faria; VEIGA, Viviane Santos de Oliveira; VIDOTTI, Silvana Aparecida Borsetti Gregório; HENNING, Patrícia; SAYÃO, Luís Fernando (org.). **FAIR Principles Applied To Research Data Management**: Brazilian Experiences. Brasília, DF: Editora Ibict, 2024. cap. 13, p. 155-165. DOI: 10.22477/9788570131959.cap13.